

An Interior Intelligent Design System Based on GAN and 3D Scene Automatic Generation Technology

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Abstract: To address the inefficiencies, high costs, and limitations in spatial rationality and automation prevalent in traditional and existing intelligent interior design approaches, this study proposes and implements an end-to-end intelligent interior design system. The system integrates a deep convolutional Generative Adversarial Network (GAN) for automated floor plan layout generation with an automatic 3D scene generation module, facilitating a seamless transition from 2D layouts to immersive 3D visualizations. The proposed GAN model incorporates class-aware convolutional layers and a spatial constraint loss function to enhance layout rationality and diversity. Experiments demonstrate that the proposed method achieves high layout accuracy (96.78%) and low furniture overlap (7.28%) on public datasets, while maintaining robust 3D reconstruction accuracy (84.36%) and precise model alignment. System performance tests show real-time rendering capability under concurrent user loads. This research provides an efficient automated solution that enhances design productivity, supports visual decision-making, and offers practical value for project management in interior design applications.

Keywords: Intelligent interior design; generative adversarial network (GAN); 3D scene generation technology; automation system; layout method.

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1. Introduction

The demand for personalized and creative interior design solutions is growing rapidly (Almaz et al., 2024). The traditional design process relies on the designer's experience, which is inefficient and costly (Huang, 2024). GAN can generate high-quality, diverse images and 3D models through adversarial training of generators and discriminators (AlZu'bi et al., 2024). Its successful application in image generation, style transfer and other fields has provided strong technical support for the automation and intelligence of interior design (Xiong et al., 2025).

Automatic generation technology based on GAN has become a research hotspot (Wang, 2025). Wu Z et al. proposed a customized style interior design framework grounded in GAN. The framework adopts a two-stage generative model and is trained through loss functions. The results showed that the framework was fast and effective in generating schemes (Wu et al., 2024). Zhu et al. (2023) introduced a method for generating multiple layout designs based on a conditional GAN. This approach uses conditional convolution and attention adaptation modules to construct a generator. The results showed that it outperformed existing methods across multiple datasets. Deshmukh et al. (2025) proposed an AI interior design system based on GANs to address the difficulty of real-time visualization in current interior design. The system combined text descriptions with spatial constraints to generate customized interior layout visualizations. The results showed that the system could effectively generate high-quality interior design previews. Kang et al. (2023) proposed a systematic interior design method that combines deep convolutional networks and GANs. The method used deep convolutional networks to identify image features and used GANs to automatically generate new shapes. The results showed that this method could effectively inspire designers and increase the diversity of interior furniture design. Preethi et al. (2024) proposed a method for replacing indoor wall colors using a gradient-based approach and GANs. The findings demonstrated that the average classification accuracy of this approach was as high as 99.33%.

In addition, the automatic generation of 3D scenes can automatically construct realistic 3D interior scenes based on user needs (Yi and Bhattacharjee, 2023). This technology allows users to more intuitively experience the effects of design solutions during the design process (Huang et al., 2023). Gao et al. (2023) introduced a hierarchical graph network for generating 3D interior scenes. They used a variational autoencoder based on a conditional recurrent neural network for

generation. This method could generate realistic 3D scenes with reasonable layout and fine-grained geometry in one go. Yang et al. (2025) proposed a dual-branch diffusion model to address the problem that existing 3D scene generation methods rely on a single text input. The model integrated text and visual information by constructing a mixed modal graph. The results showed that this method could generate a more coherent scene layout. Pintore et al. (2023) introduced an end-to-end deep learning method for 3D interior scenes. This method jointly estimated depth and room structure and designed a specific loss function, placing the main computation during training to achieve lightweight inference. Results showed that this method could generate new perspectives at interactive rates and outperform the best existing solutions in terms of latency and prediction accuracy.

Numerous academics have conducted extensive research on GAN-based indoor layout generation and 3D scene modeling, achieving significant breakthroughs. However, existing interior design methods still have the following defects: layout generation lacks spatial rationality constraints, 3D scene generation relies on manual intervention, system integration is limited, and end-to-end automated design is difficult to achieve. In view of this, the research aims to build an end-to-end indoor intelligent design system by integrating GANs and 3D scene automatic generation technology to address the pain points of low efficiency, high cost, and insufficient spatial planning rationality in traditional design. The innovation of the research lies in proposing an end-to-end integrated intelligent interior design system architecture. This architecture integrates an improved deep convolutional GAN layout-generation module with a geometric rule-based automatic 3D scene-generation module, achieving full automation from inputting floor plans to outputting high-quality 3D scenes. This work addresses shortcomings in existing methods, including limited constraints on layout rationality, reliance on manual intervention for 3D generation, and low system integration, by providing an efficient and scalable automation solution for interior design.

To guide the development and evaluation of the proposed system, this study is structured around the following research questions: (1) How can an improved deep convolutional GAN architecture effectively integrate spatial constraints and category-aware modeling to enhance the rationality and diversity of automated furniture layout generation? (2) What computational framework can enable seamless, automated conversion from 2D layout plans to visually consistent and geometrically accurate 3D indoor scenes? (3) Can an integrated, end-to-end intelligent design system maintain high layout accuracy, 3D reconstruction quality, and real-time rendering performance under practical user concurrency and occlusion conditions? By addressing these research questions, this work aims to develop and validate a fully automated interior design pipeline that bridges the gap between layout generation and immersive 3D visualization while ensuring practical usability and system-level robustness.

2. Methodology

This paper proposes a method for intelligent layout design of indoor floor plans based on a deep convolutional GAN, aiming to achieve efficient and diverse automatic layout of indoor furniture. It then constructs a model for automatic generation of indoor 3D scenes and proposes an intelligent interior design system.

2.1. Intelligent Layout Design Method for Indoor Furniture Plans Based on Deep Convolutional GAN

In interior furniture layout design, traditional methods are inefficient and difficult to meet personalized and diversified needs. GAN has shown great potential in image generation and layout synthesis (Xu et al., 2024). However, existing GAN-based layout generation methods suffer from insufficient spatial rationality and weak control over details (Tang et al., 2024). Therefore, this study introduces an intelligent layout design approach grounded in a deep convolutional GAN to enable efficient, reasonable automatic generation of interior furniture floor plans. This method is based on the pix2pix network and uses a deep convolutional GAN. When constructing the generator of the pix2pix network model, its input-output relationship and parameter structure need to be clearly defined (Pratap et al., 2025). The probability of its generator output is shown in Eq. (1).

$$P = G(I_s; \theta_G) \quad (1)$$

In Eq. (1), P is the output of the generator. The G is the generator function. The I_s is the input data, and θ_G is the trainable parameters of the generator. The schematic diagram of the generator structure of the pix2pix network model is shown in Fig. 1.

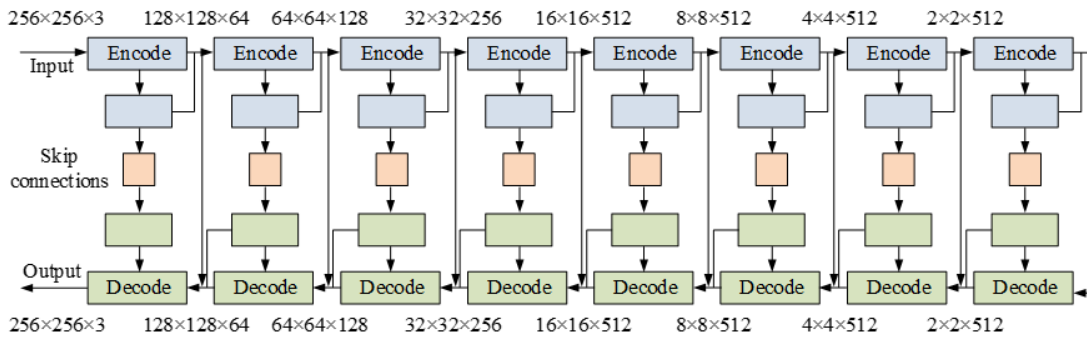


Fig. 1. Schematic diagram of generator structure for pix2pix network model

In Fig. 1, the generator of the pix2pix network model uses an encoder-decoder architecture, with the decoder performing upsampling to restore the original size. Skip connections are used between the encoder and decoder to transfer feature

information, preserving details. To accurately predict the layout of different furniture categories, independent convolutional channels are designed at the end of the generator and decoder, as shown in Eq. (2).

$$P_c(x, y) = \sigma(\text{Conv}_c(G_{\text{dec}}(I_s))) \quad (2)$$

In Eq. (2), $P_c(x, y)$ represents the probability of a furniture category c appearing at pixel location (x, y) . The σ represents the Sigmoid function. The Conv_c represents the independent convolutional layer for category c . While the $G_{\text{dec}}(I_s)$ represents the Feature Map (FM) obtained by upsampling the input I_s from the decoder portion of the generator. To maintain feature symmetry between the encoder and decoder, the study adds a symmetric convolutional layer, as shown in Eq. (3).

$$F_{\text{enc}} = \text{Conv}_{\text{sym}}(\text{Enc}(I_s)) \quad (3)$$

In Eq. (3), F_{enc} represents the enhanced encoder FM. Conv_{sym} represents the symmetric convolutional layer, and $\text{Enc}(I_s)$ represents the encoder. The study uses depthwise separable convolutions in the decoder to maintain the model's expressive power. Its calculation is shown in Eq. (4).

$$h_{k,i,j} = \sum_{m,n} K_{k,m,n} \cdot h_{k,i+m,j+n} \quad (4)$$

In Eq. (4), $h_{k,i,j}$ is the value of the output FM at the channel k , spatial position (i, j) . The k represents the channel index. The m, n represent the offset indexes inside the convolution kernel. The $K_{k,m,n}$ represents the depth convolution kernel. The $h_{k,i+m,j+n}$ represents the value of the input FM at the channel k , position $(i + m, j + n)$. After completing the depth convolution, it is necessary to fuse the information of each channel through point-by-point convolution, as shown in Eq. (5).

$$h'_{k',i,j} = \sum_k W_{k',k} \cdot h_{k,i,j} \quad (5)$$

In Eq. (5), $h'_{k',i,j}$ represents the value of the FM output after point-by-point convolution in the channel k' , position (i, j) . The k' represents the output channel index. The $W_{k',k}$ represents the weight of point-by-point convolution. The $h_{k,i,j}$ represents the value of the FM output by depth convolution in the channel k , position (i, j) . The optimized generator structure and depth separable convolution operation diagram of pix2pix network model are shown in Fig. 2.

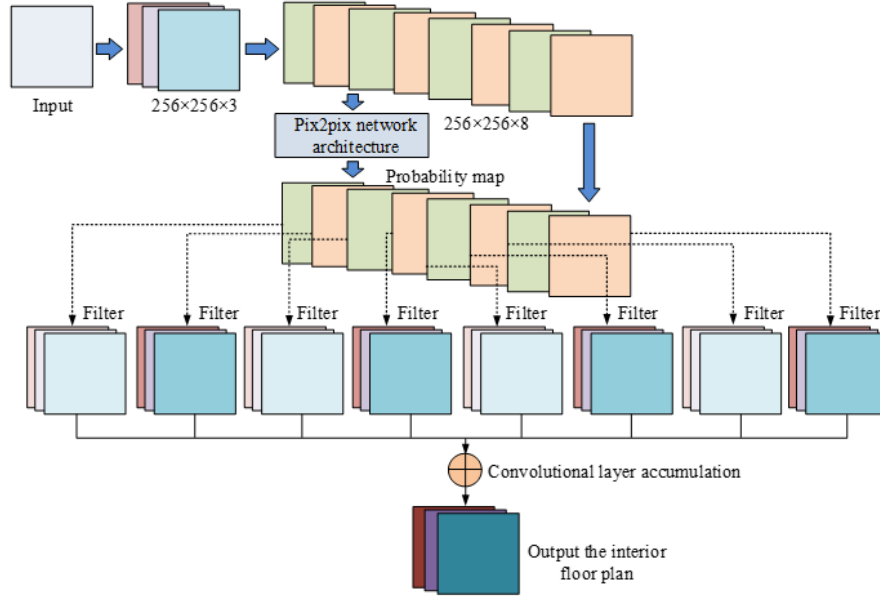


Fig. 2. Optimized pix2pix generator with depthwise separable convolution

In Fig. 2, the input to the network model is a $256 \times 256 \times 3$ image, and the output is a multichannel probability map with size $256 \times 256 \times 8$. The generator introduces a multi-channel convolutional layer at the end of the decoder, increasing the number of output channels to 8, with each channel corresponding to the layout probability prediction of a type of furniture (Xuan et al., 2024). Then multiple independent filters are used to process each input channel separately, completing spatial feature extraction. A pointwise convolutional layer is used to fuse features across multiple channels, and the resulting output can be used to produce a complete indoor floor plan. To achieve end-to-end furniture category layout prediction, the study uses the PatchGAN architecture to assess the authenticity of local image regions (Chen et al., 2023). Its expression is shown in Eq. (6).

$$\begin{cases} P_c = \text{Sigmoid}(G(x)_c) \\ D(y) = \sigma(V \cdot y + d) \end{cases} \quad (6)$$

In Eq. (6), P_c is the layout probability map of the furniture of the c th category. The $G(x)_c$ is the original response of the output channel of the generator. The x is the input of the generator. The $D(y)$ is y the judgment result of the discriminator on the input. The V is all the convolution kernel weights in the discriminator. The y is the input image of the discriminator. The d is the bias term. The adversarial loss function between the generator and the discriminator adopts the standard binary cross-entropy form as shown in Eq. (7) (Khan and Yasin, 2023).

$$L_{\text{adv}}(G, D) = E_{x,y}[\log D(x, y)] + E_x[\log(1 - D(x, G(x)))] \quad (7)$$

In Eq. (7), $L_{\text{adv}}(G, D)$ represents the adversarial loss between the generator G and the discriminator D . E represents the expected value. The $D(x, y)$ represents the output of the discriminator for the real sample (x, y) , and $G(x)$ represents the forged layout map generated by the generator. To ensure that the layout map produced by the generator closely matches the real annotated layout at the pixel level, the study introduces a layout consistency loss, as shown in Eq. (8).

$$L_{\text{layout}} = \sum_{c=1}^C \|P_c - Y_c\|_2^2 \quad (8)$$

In Eq. (8), L_{layout} is the layout consistency loss. The C is the total number of furniture categories, and Y_c is the binary distribution map of the furniture category c in the ground-truth layout annotation. Furniture items are categorized into eight functional classes based on typical indoor usage and geometric attributes: Beds, sofas, tables, chairs, cabinets, desks, shelves, and lighting fixtures. Each category is associated with a distinct convolutional channel in the generator, enabling independent probability prediction and layout optimization. This study further introduces a spatial constraint loss term to address overlap in furniture layout. Its expression is shown in Eq. (9).

$$L_{\text{overlap}} = \sum_{i \neq j} \sum_{u,v} \max(0, P_i(u, v) + P_j(u, v) - 1) \quad (9)$$

In Eq. (9), the L_{overlap} represents the spatial constraint loss. The (u, v) represents the pixel coordinate in the image. The $\max(0, \cdot)$ represents the hinge loss form. Finally, the study combines the adversarial loss, layout consistency loss, and spatial constraint loss with certain weights to form the total loss function.

2.2. 3D Scene Automatic Generation Technology and System Implementation for Interior Intelligent Design

After designing the layout of interior furniture floor plans using deep convolutional GANs, it is necessary to further construct their 3D scenes to improve the intuitiveness and interactivity of the design scheme (Zhang and Thienmongkol, 2024). However, existing 3D scene generation methods largely rely on manual modeling or single-modal inputs, making it difficult to achieve an end-to-end automated conversion from layout to scene (Zhao and Zhao, 2022). Therefore, this study develops a set of 3D scene automatic generation models and integrates them into the interior intelligent design system to enable a seamless connection from layout generation to 3D visualization.

The 3D scene generation model enables 3D reconstruction of elements such as furniture, walls, and floors by computing geometric transformation parameters and lighting settings (Fan et al., 2024). The position of the model in the world coordinate system (WCS) is shown in Eq. (10).

$$T_c = (x_c \cdot s_x, y_c \cdot s_y, 0) \quad (10)$$

In Eq. (10), T_c represents the translation vector in the 3D world. The x_c, y_c represent the plane coordinates of the center of the furniture in the local image, and s_x, s_y represent the scale factors. To enhance scene diversity, the furniture needs to be rotated and scaled, as shown in Eq. (11).

$$S_c = \left(\frac{w'_c}{w_c}, \frac{h'_c}{h_c}, \frac{d'_c}{d_c} \right) \quad (11)$$

In Eq. (11), S_c represents the 3D scaling vector. The $w_c, h_c,$ and d_c represent the initial width, height, and depth of the furniture 3D model. The $w'_c, h'_c,$ and d'_c represent the width, height, and depth that the furniture is expected to occupy in the scene, respectively. The rotation angle is obtained by the furniture orientation in the layout or by random sampling, as shown in Eq. (12).

$$R_c = \begin{pmatrix} \cos \theta_c & 0 & \sin \theta_c \\ 0 & 1 & 0 \\ -\sin \theta_c & 0 & \cos \theta_c \end{pmatrix} \quad (12)$$

In Eq. (12), R_c represents the rotation matrix around the Y axis. The θ_c represents the angle of rotation around the Y axis. The walls and floors are considered as regular polygons and are fitted using multiple rectangular patches. Its expression is shown in Eq. (13).

$$\begin{cases} V_{\text{wall}} = \{(b_x, b_y, 0), (b_x, b_y, H_{\text{wall}}) | b \in B\} \\ V_{\text{floor}} = \{(b_x, b_y, -T_{\text{floor}}) | b \in B\} \end{cases} \quad (13)$$

In Eq. (13), V_{wall} and V_{floor} represent the 3D vertex sets of the wall and floor, respectively. B represents the boundary point set of the layout diagram. The b_x, b_y represent the X-coordinate and Y-coordinate of the boundary point. The H_{wall} represents the height of the wall, and T_{floor} represents the lower surface of the floor. The lighting setting uses a point light source to simulate indoor lighting (Ren et al., 2023). Its light intensity is shown in Eq. (14).

$$I_p = \frac{I}{1 + \varepsilon \cdot \|p - L_p\|^2} \quad (14)$$

In Eq. (14), I_p represents the intensity of light received at the scene midpoint p . The I represents the initial intensity of the light source. The ε represents the attenuation coefficient. The L_p represents the position of the point light source in the WCS. This study uses perspective projection to map a 3D scene to a two-dimensional image, as shown in Eq. (15).

$$\begin{cases} V = \text{lookat}(A, T, U) \\ F = \text{perspective}(f_{ov}, a_{\text{spect}}, n, f) \end{cases} \quad (15)$$

In Eq. (15), V and F represent the view matrix and perspective projection matrix, respectively. A represents the camera's position in the WCS. The T represents the target point the camera is aiming at. The U represents the direction vector in the WCS. f_{ov} represents the vertical viewing angle. The a_{spect} represents the aspect ratio. The n and f represent the distances to the near and far clipping planes. The perspective represents the standard perspective projection function. Based on the aforementioned 3D scene automatic generation model, a complete intelligent interior design system is designed. This system adopts a front-end and back-end separation architecture, capable of fully automated processing from floor plan input to 3D scene generation, and supporting user-interactive editing. A schematic diagram of the 3D scene reconstruction framework and interior design system modules is shown in Fig. 3.

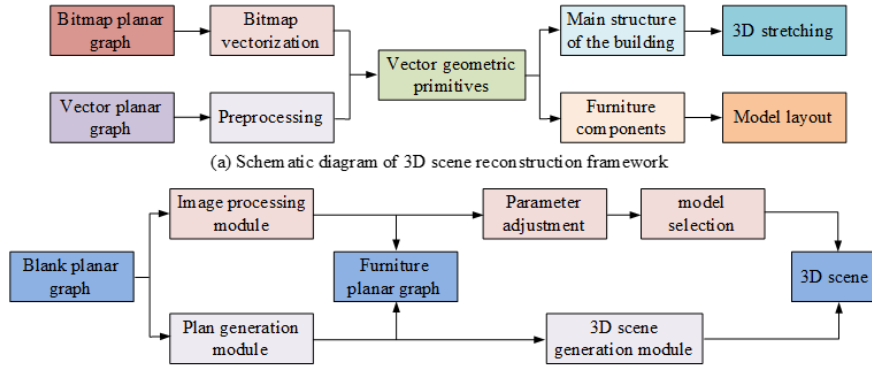


Fig. 3. Schematic diagram of 3D scene reconstruction framework and interior design system module

In Fig. 3(a), the 3D scene reconstruction method first obtains geometric shapes through vector analysis. These shapes are then decomposed into the main components of the interior furniture, and a stretching method is used to generate the 3D scene. In Fig. 3(b), the interior design system module mainly includes a front-end module and a back-end module. In the front-end module, the image processing module receives blank floor plans or existing room images uploaded by users; the parameter adjustment module customizes the generation parameters; and the model selection module selects or replaces 3D models of furniture, decorations, and other objects from a preset model library. In the back-end module, the interior floor plan generation module converts a blank input floor plan or room image into a floor plan with furniture layout. The 3D scene generation module automatically extracts geometric parameters from the layout results, enabling the conversion from 2D layout to 3D scene. The process flow of the intelligent interior design system is presented in Fig. 4.

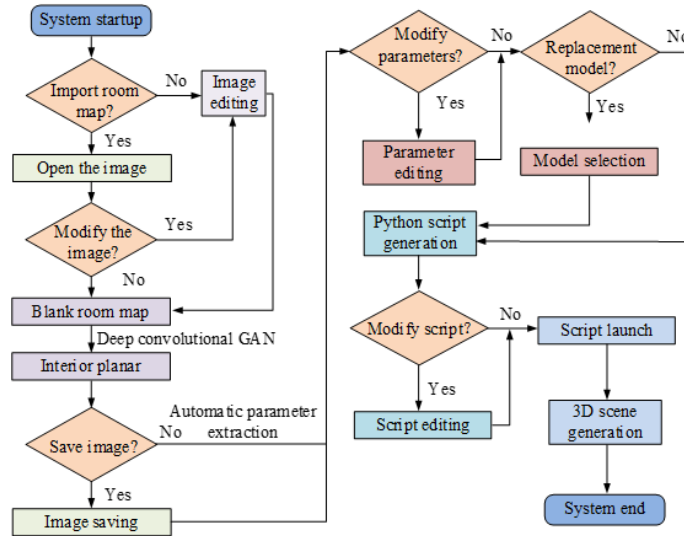


Fig. 4. Process diagram of indoor intelligent design system

Fig. 4 illustrates the workflow of the intelligent interior design system. After launching the system, users can import or edit a room image to generate a blank floor plan. The deep convolutional GAN model automatically generates a floor plan of the interior furniture and extracts parameters. Users can save the image, adjust parameters, or replace the model. The system automatically generates a script based on the settings and ultimately outputs a visualization.

3. Results and Analysis

The performance of the introduced intelligent layout design approach for indoor floor plans was verified to evaluate its layout accuracy and rationality. The effect of automatically generating 3D scene models was then evaluated, and the proposed intelligent interior design system was tested.

3.1. Performance Verification of the Intelligent Layout Design Method for Indoor Floor Plans

To validate the performance of the introduced intelligent layout design approach for interior furniture floor plans, experiments were conducted on the public datasets LSUN and Structured3D. The LSUN dataset contains multiple real-world indoor scene images, each with accurate, pixel-level room layout annotations. The Structured3D dataset contains diverse indoor scenes covering a variety of layouts, decoration styles, and furniture configurations. The introduced approach was compared with existing state-of-the-art methods, including Customized Style Interior Design Generative Adversarial Network (CSID-GAN), Graph Convolutional Network for Hierarchical Scene Layout Generation (GCN-HSLG), and Context-Aware Furniture Arrangement using Reinforcement Learning (CAFA-RL). The experimental environment was as follows: the central processing unit was Intel Xeon Gold 6248R, the graphics processor was NVIDIA RTX 4090, the memory was 128GB DDR4, and the operating system was Ubuntu 20.04 LTS. The example indoor scene images of the LSUN and Structured3D datasets are shown in Fig. 5.



Fig. 5. Example indoor scene images of LSUN and Structured3D datasets

Higher layout accuracy and lower furniture overlap rate can directly improve design quality, as reflected in the reasonable allocation of functional space, compliance with ergonomic principles, and visual coordination. From a usability perspective, a lower overlap rate can reduce reliance on manual post-editing, thereby improving designers' work efficiency and user satisfaction in interactive applications.

To verify the system's robustness to key parameter settings and to provide a basis for design selection, sensitivity analysis was conducted on key parameters, including adversarial loss weights, spatial constraint weights, overlap thresholds, and furniture categories. The results are shown in Table 1. In Table 1, the system achieved optimal performance when the adversarial loss weight was 1.0, the spatial constraint weight was 0.5, the overlap threshold was 5 pixels, and the furniture category was 8. The layout accuracy reached 96.78%, and the furniture overlap rate was only 7.28%. Adjusting any parameter would cause performance fluctuations. For example, when the spatial constraint weight was reduced to 0.2, the overlap rate increased to 9.45%, and when the number of furniture categories was increased to 10, the accuracy slightly decreased to 95.92%. This indicated that the system was sensitive to parameter changes, but the selected configuration had significant robustness, verifying the rationality of parameter settings.

This study analyzed the layout accuracy of different intelligent layout design methods for different furniture counts on the LSUN and Structured3D datasets. The outcomes are presented in Fig. 6. In Fig. 6(a), in the LSUN dataset, when the number of furniture was 1, the layout accuracy of CSID-GAN, GCN-HSLG, CAFA-RL, and the proposed method was 92.12%, 90.03%, 93.86%, and 95.71%, respectively. When the number of furniture pieces was 11, the layout accuracy of the four methods was 82.37%, 76.58%, 86.78%, and 92.36%, respectively. In Fig. 6(b) of the Structured3D dataset, when the number of furniture items reached 11, the layout accuracies of CSID-GAN, GCN-HSLG, CAFA-RL, and the proposed method were 87.28%, 82.66%, 92.04%, and 96.78%, respectively. The findings demonstrated that the proposed method could still maintain high layout rationality and stability in complex scenes with multiple pieces of furniture.

The study further compared the furniture overlap rate (FOR) and structural similarity index (SSIM) of different methods on the two datasets. The outcomes are presented in Fig. 7. In Fig. 7(a), CSID-GAN, GCN-HSLG, and CAFA-RL achieved FORs of 12.41%, 15.76%, and 13.92% on the LSUN dataset, and 10.94%, 14.33%, and 12.15% on the Structured3D dataset, respectively. The multi-protocol method achieved FORs of 8.05% and 7.28% on the two datasets, respectively. In Fig. 7(b),

the SSIMs of the four methods were 0.823, 0.785, 0.801, and 0.892 on the LSUN dataset, and 0.846, 0.808, 0.829, and 0.905 on the Structured3D dataset, respectively. The results showed that the introduced approach outperformed advanced existing methods in maintaining the rationality of the layout structure and visual authenticity.

Table 1. Sensitivity analysis of key parameters

Parameters	Values	Layout Accuracy (%)	Furniture Overlap Rate (%)
Adversarial loss weight	0.5	95.45	8.67
	1.0	96.78	7.28
	1.5	96.20	7.95
Spatial constraint weight	0.2	95.12	9.45
	0.5	96.78	7.28
	0.8	96.01	8.11
Overlap threshold	3	96.50	10.21
	5	96.78	7.28
	8	96.24	7.07
Furniture category granularity	6	94.58	8.02
	8	96.78	7.28
	10	95.92	7.12

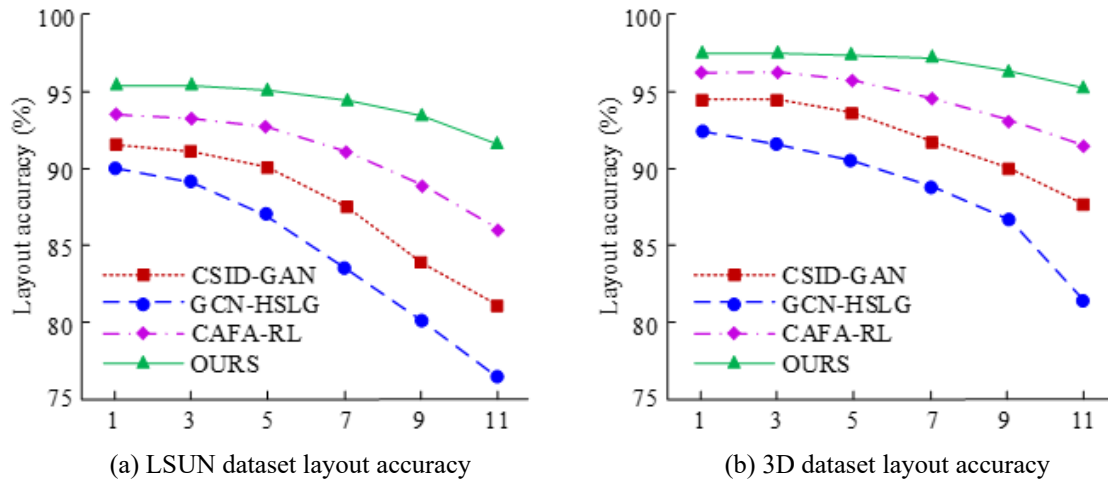


Fig. 6. Layout accuracy of different intelligent layout design methods under different furniture quantities

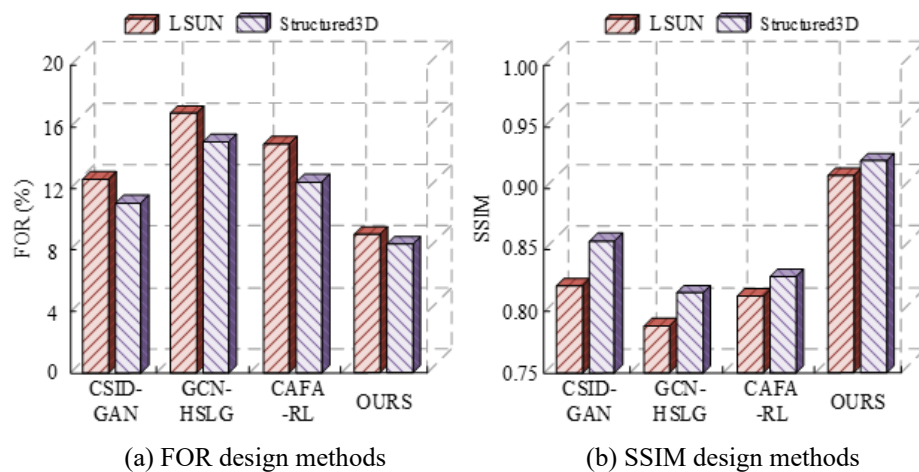


Fig. 7. Comparison of FOR and SSIM for different intelligent layout design methods

To evaluate the generalization ability of the proposed method across different functional spaces, the study analyzed category accuracy across room types and layout design methods in two datasets. The room types included living rooms, bedrooms, kitchens, and bathrooms. The outcomes are presented in Table 2. The introduced approach achieved accuracies of 88.68%, 90.32%, 86.16%, and 92.89% for living rooms, bedrooms, kitchens, and bathrooms, respectively, on the LSUN dataset, outperforming all other compared methods. In the Structured3D dataset, the proposed method achieved the highest

category accuracy. These results demonstrated that the proposed method exhibited good generalization ability and stable layout generation quality across different functional rooms.

3.2. Evaluation of 3D Scene Automatic Generation and Testing of Interior Intelligent Design System

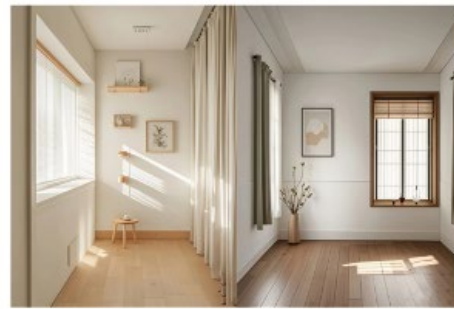
To confirm the validity of the introduced automatic 3D scene generation model and explore the overall performance of the intelligent interior design system, this study used the publicly available Matterport3D and ScanNet datasets as benchmarks and compared them with current mainstream models. The Matterport3D dataset contains high-quality, color-textured 3D meshes. The ScanNet dataset covers a variety of indoor scenes and annotates 3D semantic information from multiple views. The comparison models included the Mixed-Modality Graph for Geometry-Controllable 3D Indoor Scene Generation (MMGDreamer), the Hierarchical Scene Generation with Conditional VAE (CVAE-HSG), and the Diffusion-based Multi-modal Scene Generation (DMSG). The example indoor scene images of Matterport 3D and ScanNet datasets are shown in Fig. 8.

Table 2. Comparison of accuracy category for different room types under various layout design methods

Datasets	Methods	Living room	Bedroom	Kitchen	Bathroom
LSUN	CSID-GAN	84.52	86.24	81.69	89.11
	GCN-HSLG	80.17	82.85	77.53	85.86
	CAFA-RL	82.81	84.55	79.87	87.47
	OURS	88.68	90.32	86.16	92.89
Structured3D	CSID-GAN	86.33	88.01	83.56	90.93
	GCN-HSLG	82.57	84.73	79.33	87.52
	CAFA-RL	84.91	86.61	81.82	89.25
	OURS	90.59	92.13	87.96	94.58



(a) Indoor scene from Matterport3D



(b) Indoor scene from ScanNet datasets

Fig. 8. Example indoor scene images from Matterport3D and ScanNet datasets

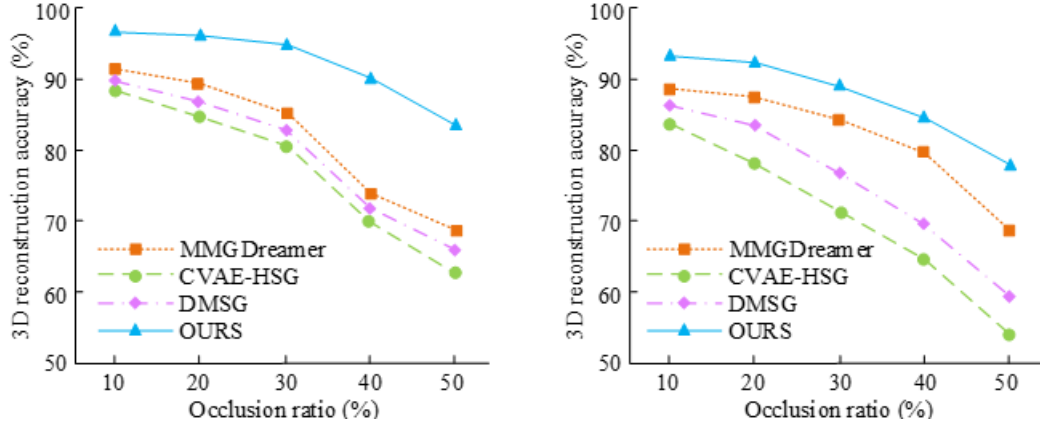
Maintaining robust 3D reconstruction accuracy and fine model alignment error under high-occlusion conditions not only verified the process's technical reliability but also supported decision-making based on visual preview in design practice. Accurate 3D preview enabled clients and designers to intuitively evaluate spatial proportions, material coordination, and lighting effects in the early stages of design, thereby reducing costly modifications and improving the approval rate of solutions.

The study analyzed the accuracy of 3D reconstruction across different 3D scene generation models under varying occlusion ratios on the Matterport3D and ScanNet datasets. The outcomes are presented in Fig. 9. In Fig. 9(a), with a 10% occlusion ratio on the Matterport3D dataset, the 3D reconstruction accuracy of MMGDreamer, CVAE-HSG, DMSG, and the proposed model was 92.15%, 88.64%, 89.72%, and 97.68%, respectively. When the occlusion ratio was 50%, the accuracies were 68.27%, 63.68%, 67.59%, and 84.36%, respectively. In Fig. 9(b), when the occlusion ratio was 50%, the 3D reconstruction accuracy of the four models on the ScanNet dataset was 68.22%, 54.17%, 59.65%, and 78.36%, respectively. The results showed that the proposed 3D scene generation model was more robust to occlusion and could more accurately reconstruct complete indoor 3D scenes from partially visible information.

The study compared the model alignment error (MAE) and light consistency error (LCE) of different models on the two datasets. The outcomes are presented in Fig. 10. In Fig. 10(a), the MAEs of MMGDreamer, CVAE-HSG, and DMSG on the Matterport3D dataset were 12.52mm, 15.20mm, and 11.81mm, respectively, and on the ScanNet dataset were 13.12mm, 16.01mm, and 12.35mm, respectively. Therefore, the MAEs of the models on the two datasets were 9.14mm and 9.36mm, respectively. In Fig. 10(b), the LCEs of the four models on the Matterport3D dataset were 8.32%, 10.17%, 7.90%, and 6.15%, respectively, and on the ScanNet dataset were 8.72%, 10.81%, 8.13%, and 6.50%. The findings demonstrated that the proposed model could not only achieve more accurate geometric alignment but also generate more consistent and realistic 3D scenes with lighting effects.

To explore the real-time rendering performance of the proposed intelligent interior design system, the study analyzed the average rendering frame rates of different models in two real-world scenarios: residential living room design and office space layout. The outcomes are presented in Fig. 11. In Fig. 11(a), in the residential living room design scenario, when the

concurrent user count was 25, the average rendering frame rates of MMGDreamer, CVAE-HSG, DMSG, and the proposed model were 13.21 FPS, 6.77 FPS, 15.02 FPS, and 48.58 FPS, respectively. In Fig. 11(b), in the office space layout scenario, when the concurrent user count was 25, the average rendering frame rates of MMGDreamer, CVAE-HSG, and DMSG were 27.62 FPS, 16.05 FPS, and 30.17 FPS, respectively, while the average rendering frame rate of the proposed model was 58.92 FPS. In Fig. 11(c) and 11(d), the proposed intelligent interior design system not only maintains high generation quality but also provides a smoother real-time rendering experience even under high concurrent user loads. The excellent frame rate achieved by the proposed system is attributable to its optimized front-end and back-end separation architecture and efficient 3D scene generation pipeline, which together reduce computational overhead and enable responsive interaction in practical design applications. These results demonstrated that the proposed intelligent interior design system could ensure generation quality and provide a smoother real-time rendering experience.



(a) Accuracy of 3D reconstruction using Matterport 3D (b) Accuracy of 3D reconstruction using ScanNet

Fig. 9. 3D reconstruction accuracy of various models under different occlusion ratios

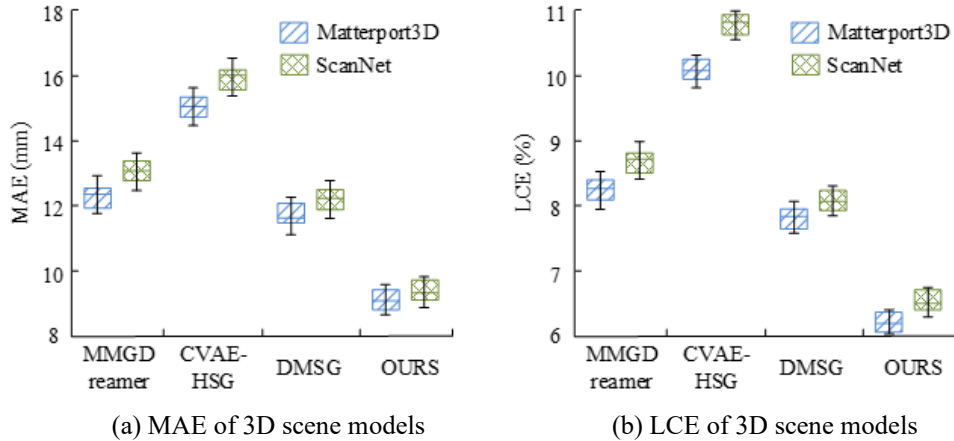


Fig. 10. Comparison results of MAE and LCE for different 3D scene generation models

To further assess the design quality, user experience, and practical deployment benefits of the proposed intelligent interior design system, a user study and an efficiency analysis were conducted. Twenty professional interior designers and thirty non-expert users were recruited to evaluate the system through a series of standardized tasks involving the generation and modification of layouts for residential living rooms and office spaces. The evaluation metrics included subjective ratings on a 5-point Likert scale (1=Very Poor, 5=Excellent) and objective efficiency measures. The results are shown in Table 3. In Table 3, the system performed exceptionally well across all dimensions. In terms of design quality, the scores for layout rationality and visual realism were both higher than 4.3. The usability score in user experience was 4.69 points. The deployment benefits were outstanding, with a 65% reduction in task completion time compared to traditional processes and a 55% reduction in design iterations. The adoption intention scores for expert and non-expert users were 4.40 and 4.60, respectively, indicating that the system was practical and well accepted.

4. Conclusion

This study proposed an intelligent interior design system based on a deep convolutional GAN and the automatic generation of 3D scenes. Class-aware convolutional layers and a spatial constraint loss function were introduced to improve layout accuracy. First, the proposed deep convolutional GAN with class-aware layers and spatial loss significantly improved layout rationality and diversity, achieving up to 96.78% accuracy and only 7.28% overlap. Second, the geometric and lighting-based 3D reconstruction pipeline enabled fully automated, accurate conversion from 2D layouts to consistent 3D scenes, with MAE below 9.36mm. Finally, the integrated system demonstrated robust real-time performance under concurrent use

(58.92 FPS), confirming its practical viability for interactive design applications. These results demonstrated that the proposed intelligent interior design system could efficiently generate interior design solutions with reasonable layouts, realistic visuals, and functional requirements, and achieved automated, high-quality conversion from 2D layouts to 3D scenes. Automated 2D-to-3D conversion enabled rapid prototyping, allowing designers and project managers to visualize and compare alternatives efficiently, thus supporting evidence-based design choices. The system was designed to be integrated as an assistive tool into standard design workflows, enabling designers to efficiently refine initial layouts generated by the model. This human-in-the-loop interaction paradigm facilitated rapid ideation and visualization, potentially reducing iteration cycles and enhancing collaboration between designers and clients. Based on process optimization and lifecycle theory in engineering management, full-process automation from 2D layout to 3D scene was systematically implemented, manual intervention was reduced, and project delivery efficiency and design quality were improved (Chen and Luo, 2022; Kirgizov and Kwak, 2022).

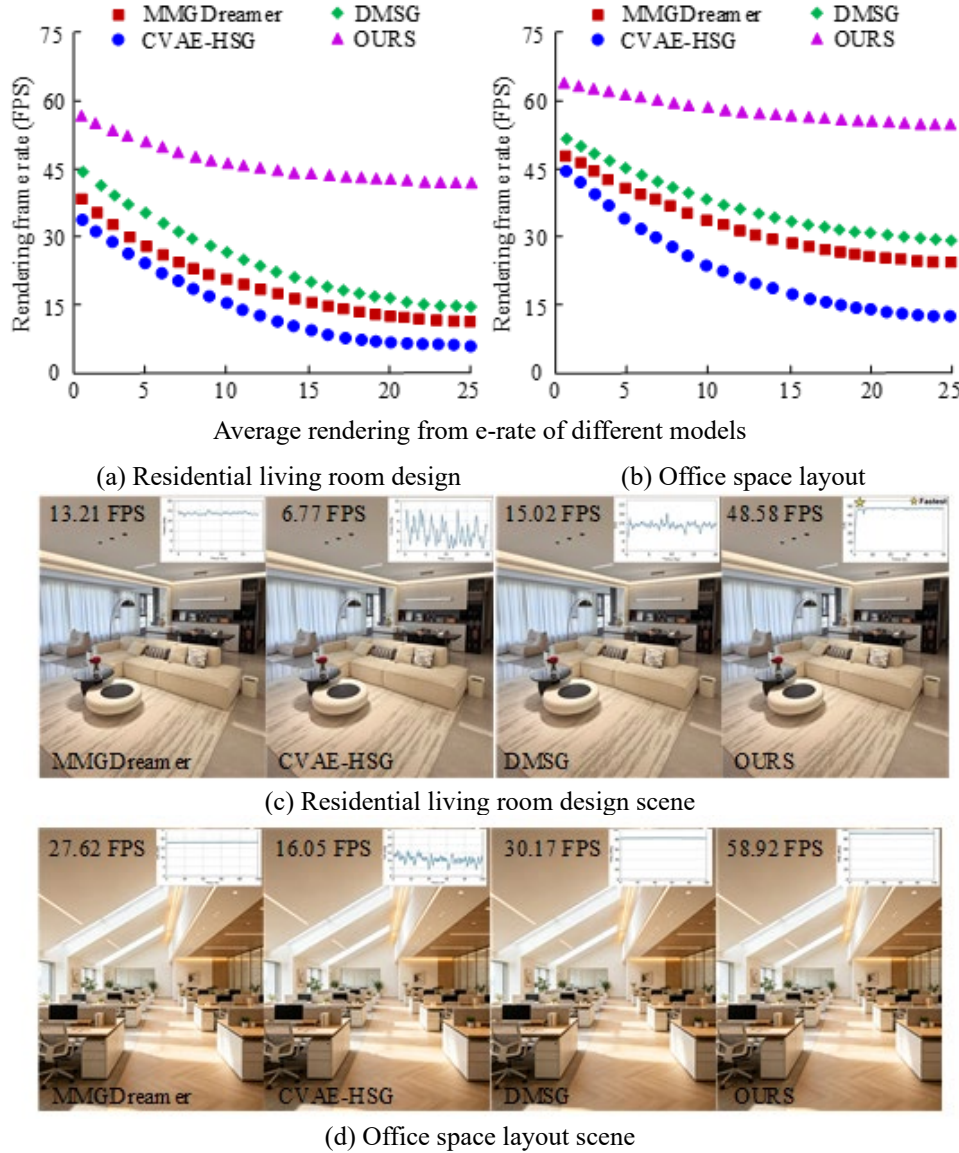


Fig. 11. Comparison of average rendering frame rates of different models in actual scenarios

The limitation of the research is that the current 3D generation module primarily relies on rule-based geometric transformations and does not integrate scene-semantic understanding capabilities. Therefore, when dealing with complex, unconventional, or highly customized indoor layouts, their flexibility and scene rationality may be limited. The performance of the proposed system depends on large-scale, well-labeled datasets, which may limit its applicability in certain fields or in data-scarce scenarios. The diversity of styles for generating layouts is limited by the distribution of training data. The current rule-based 3D reconstruction module lacks semantic understanding of the scene, which may affect its flexibility in handling unconventional layouts. Future research will explore the use of semantic perception generation methods such as graph neural networks, scene graph inference, or diffusion models to enhance the system's ability to understand and express complex layouts and abstract design intentions. Integrating style transfer and diffusion models to enhance aesthetic diversity, and introducing graph neural networks to achieve semantic-driven intelligent 3D generation. At the same time, further research will be conducted into integrating the system with BIM and project management platforms to support full-lifecycle engineering management.

Table 3. Evaluation of design quality, user experience, and deployment benefits

Evaluation Dimension	Metric	Expert Users (n=20)	Non-Expert Users (n=30)
Design Quality	Layout Rationality	4.45	4.20
	Visual Realism	4.30	4.40
	Style Consistency	4.15	4.10
User Experience	Ease of Use	4.60	4.75
	System Responsiveness	4.55	4.65
	Satisfaction with Output	4.35	4.50
	Task Completion Time (min)	8.71	12.33
Deployment Benefits	Iterations Needed for Final Design	2.10	1.82
	Willingness to Adopt	4.40	4.60

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Institutional Review Board Statement

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Declaration of Artificial Intelligence (AI) Tools

The author used AI tools solely for language editing and to improve readability. The author reviewed and verified all content and takes full responsibility for the accuracy and integrity of the manuscript.

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