

Article

Generative AI-Driven Design Method of Planar Inclined Shear Wall Components for Building Structures

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Abstract

The advancement of generative artificial intelligence (AI) has accelerated the progress of intelligent design methods for building structures. However, generative AI models struggle to design inclined shear wall components due to their limited generalization ability. To address this obstacle, this study proposes a data augmentation method for the planar layout of rotated shear wall structures. By enhancing the dataset and associated post-processing methods, the generalization ability of design methods driven by generative AI algorithms is effectively improved. Specifically, an augmented dataset by rotating non-inclined component design data was constructed, with rotation angles from 0° to 60°, to encompass inclined shear wall design scenarios. The improved generalization performance between diffusion models, generative adversarial networks, and graph neural networks was then compared. An automatic vectorization extraction method for inclined components from the generated design feature tensors is established, enabling the application of the enhanced generative AI algorithms. Moreover, algorithm performance analysis and typical case studies show that the diffusion model performs best in the inclined shear wall design task. This comprehensive analysis confirms that data augmentation significantly improves the adaptability of generative AI to inclined component design, providing a valuable reference for enhancing the generalization of data-driven AI design in building structures.

Keywords: generative AI; structural intelligent design; plan-inclined shear walls; data augmentation; image vectorization; sustainability

1. Introduction

1.1. Literature Review

Generative AI algorithms, including generative adversarial networks (GANs), diffusion models, and graph neural networks (GNNs), have been increasingly applied to the intelligent design of building structures [1].

Liao et al. [2] pioneered the use of GANs for shear wall layout design in residential buildings, establishing the feasibility of data-driven structural design. Zhao et al. [3] proposed GNN-based methods that represent building components as graphs, enabling topology-aware structural design. Gu et al. [4] introduced diffusion model-based shear wall design, achieving high-quality generation results. In addition, Wang et al. [5], Zhou et al. [6], and He et al. [7] also proposed shear wall layout algorithms based on diffusion models.

These methods have been further extended to other structural types and architectural design. Shim et al. [8] proposed an architectural floor plan generation algorithm based



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on diffusion models. Fu et al. [9,10] proposed a steel bracing layout algorithm based on generative adversarial networks. Tan et al. [11] proposed a BRB bracing reinforcement layout algorithm based on diffusion models. Zhang et al. [12] proposed structural topology generation based on graph neural networks. Leng et al. [13] further connected architectural layout generation from sketches to shear wall design using diffusion models. Zhang et al. [14] proposed an inverse design method for energy-dissipating steel plate walls based on self-supervised diffusion models. Santos and Sotelino [15] proposed a GAN-assisted layout generation method for automated structural design of industrial plants. Additionally, Fei et al. [16] proposed a structural optimization-based data enhancement method for shear wall design, which improves training data quality through optimization techniques. Related research employs neural networks to assist in optimizing structural design [17–19]. Panagiotou et al. [20] demonstrated that generative AI-based data augmentation can effectively address data scarcity in offshore jacket design. Hussain et al. [21] utilized GAN-based synthetic data augmentation to improve the prediction of cumulative plastic deformation for BRBs. In addition, a fractional-order multi-rate Kalman fusion method for structural performance warning is applied to improve structural safety through intelligent computing methods [22].

Despite these advances, significant limitations remain in existing research:

- (1) Insufficient coverage of inclined components in existing datasets. Current datasets for shear wall structural design predominantly consist of buildings with orthogonal layouts, where components are aligned with the x - and y -axes. Design cases featuring inclined shear wall components are extremely scarce, leading to a typical long-tail distribution in the data. This scarcity prevents generative AI models from effectively learning the design features of inclined components.
- (2) Poor generalization of models to irregular or inclined layouts. When the design object is expanded from orthogonal to inclined components, the entire model training process must essentially be repeated, indicating that the generalization ability of existing intelligent design algorithms is insufficient. Although some data augmentation methods have been proposed to address data scarcity in structural design [16,20,21], they focus on data quality improvement rather than expanding design object coverage. There is currently no clear research conclusion on whether generative AI algorithms can accommodate new design requirements solely through dataset enrichment without retraining.
- (3) Lack of data augmentation methods for inclined component design. While data augmentation techniques have been widely studied in computer vision, their application to structural design—particularly rotation-based augmentation for inclined component scenarios—remains unexplored. Furthermore, no systematic comparative analysis of different generative AI algorithms on inclined component design tasks has been conducted.

To address these gaps, this study proposes a rotation-based data augmentation method to construct an inclined shear wall component dataset, thereby enhancing the generalizability of data-driven AI design methods for building structures.

1.2. This Study

Specifically, this study takes the inclined shear wall component design task as an example, enhances the existing dataset, and compares the generalization capabilities of GANs, diffusion models, and GNNs on new design tasks. Herein, inclined shear wall component design refers to shear wall components that are inclined members not parallel to the planar x and y axes. In residential building structural design, to ensure good lighting, ventilation, and structural performance, the layout of architectural and structural com-

ponents is typically parallel to the planar x and y axes. However, with the development of building design and the demand for larger building spaces, inclined architectural and structural components not parallel to the x and y axes have begun to appear, and building designs with inclined components are almost non-existent in existing datasets. Generative AI algorithms have not received effective training on the design of inclined shear wall component layouts, leading to their lack of corresponding design capabilities. This study will conduct research focusing on enhancing dataset content, training generative AI models, and testing and evaluation, to demonstrate that dataset improvement can effectively improve the generalization of generative AI design algorithms for building structures.

From a sustainability perspective, the proposed AI-driven method demonstrates significant potential to optimize material distribution and minimize concrete and steel consumption. This could effectively reduce the carbon footprint of the construction sector [23,24], all while ensuring that the generated designs meet seismic safety standards [25].

2. Intelligent Design Method for Planar Inclined Shear Wall Members

In this study, “inclined shear wall component” refers exclusively to a shear wall component whose orientation is not parallel to the x - or y -axis within the horizontal (x - y) plane, that is, a component that is inclined in plan. “In-plane rotation” refers to the data augmentation operation of rotating all component coordinates around the geometric center of the floor plan within the horizontal plane, which is used to simulate building design scenarios containing inclined components.

In high-rise residential buildings, inclined shear wall members are frequently present due to architectural functional requirements (Figure 1). However, the intelligent design algorithms for shear wall structures proposed in existing studies [2–4] have not considered such inclined members. Consequently, existing intelligent algorithms are unable to perform relevant designs involving inclined shear wall layouts.

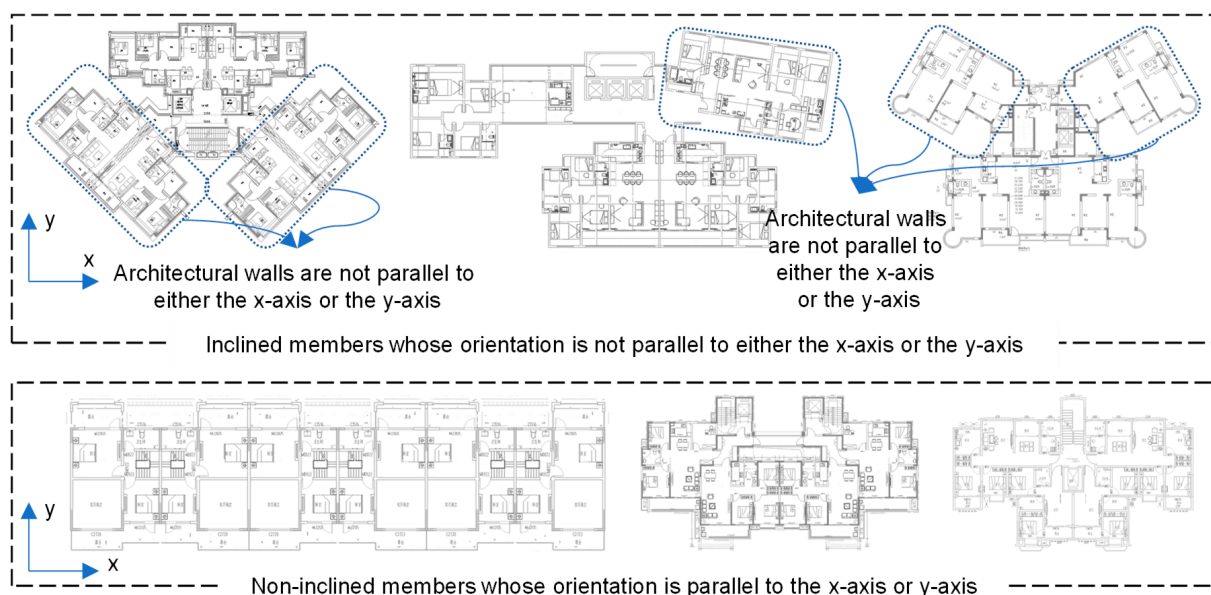


Figure 1. Floor plan design drawing of a residential building with inclined wall layout (Note: some non-English characters in the CAD drawings for architectural layout design represent the names of building functional spaces.).

Shear wall structures are predominantly used in high-rise buildings such as residential buildings and hotels. In China, due to limitations imposed by climatic conditions, a north–south orientation is predominantly adopted for architectural layouts, making design cases of inclined shear walls significantly fewer than those with non-inclined component layouts.

Consequently, the data distribution for the design of planar inclined shear wall layouts exhibits typical long-tail distribution characteristics, which is detrimental to the learning process of generative intelligent design algorithms. If the scarce design data for inclined shear walls are simply mixed with existing design drawing materials, then, due to the significant disparity in the quantity of drawings (i.e., the number of drawings for non-inclined components is tens of times greater than that for drawings with inclined shear walls), the learning outcomes of generative AI may become biased towards the features of non-inclined components, and the design of inclined shear wall layouts would act akin to noise, interfering with the learning of generative AI algorithms, leading to suboptimal design results. Therefore, this study proposes a data augmentation method based on rotating non-inclined component designs to generate inclined ones, and subsequently trains generative AI models with the augmented dataset, enabling the intelligent design of inclined shear wall component layouts by generative AI.

The specific implementation process of this research is shown in Figure 2. First, rotation augmentation of design drawing data is performed, and data features are extracted and constructed as feature matrices and graphs for input into different generative AI algorithms (Figure 2a). Subsequently, generative AI algorithms, including diffusion models, GANs, and GNNs, are developed, and model training is performed based on the constructed dataset (Figure 2b). Finally, the trained models are applied to the intelligent design of shear wall component layout, achieving intelligent design for the generation of inclined shear wall component layouts (Figure 2c).

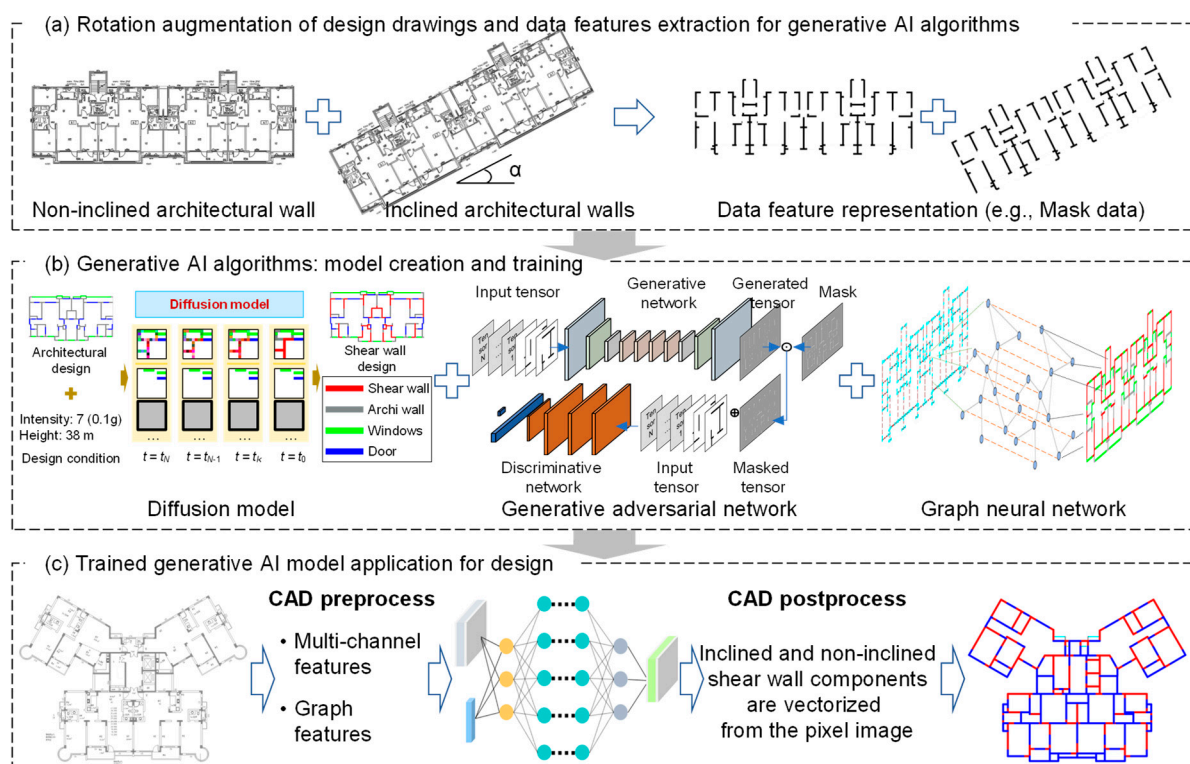


Figure 2. Intelligent design method for inclined shear wall component arrangement. (Note: some non-English characters in the CAD drawings for architectural layout design represent the names of building functional spaces.).

2.1. Inclined Shear Wall Component Layout Dataset Construction

This study collected a total of over 600 sets of CAD drawings of shear wall residential building structural designs from multiple renowned design institutes across the country. The design drawings are of high quality and rationality, and the structural design informa-

tion is quite comprehensive. Based on the developed CAD design drawing preprocessing method [26], all complex CAD data was converted into concise structured data; furthermore, according to the input data feature requirements of generative AI algorithms, feature images and graph data were constructed for subsequent generative AI model training and testing. The detailed dataset construction process is shown in Figure 3.

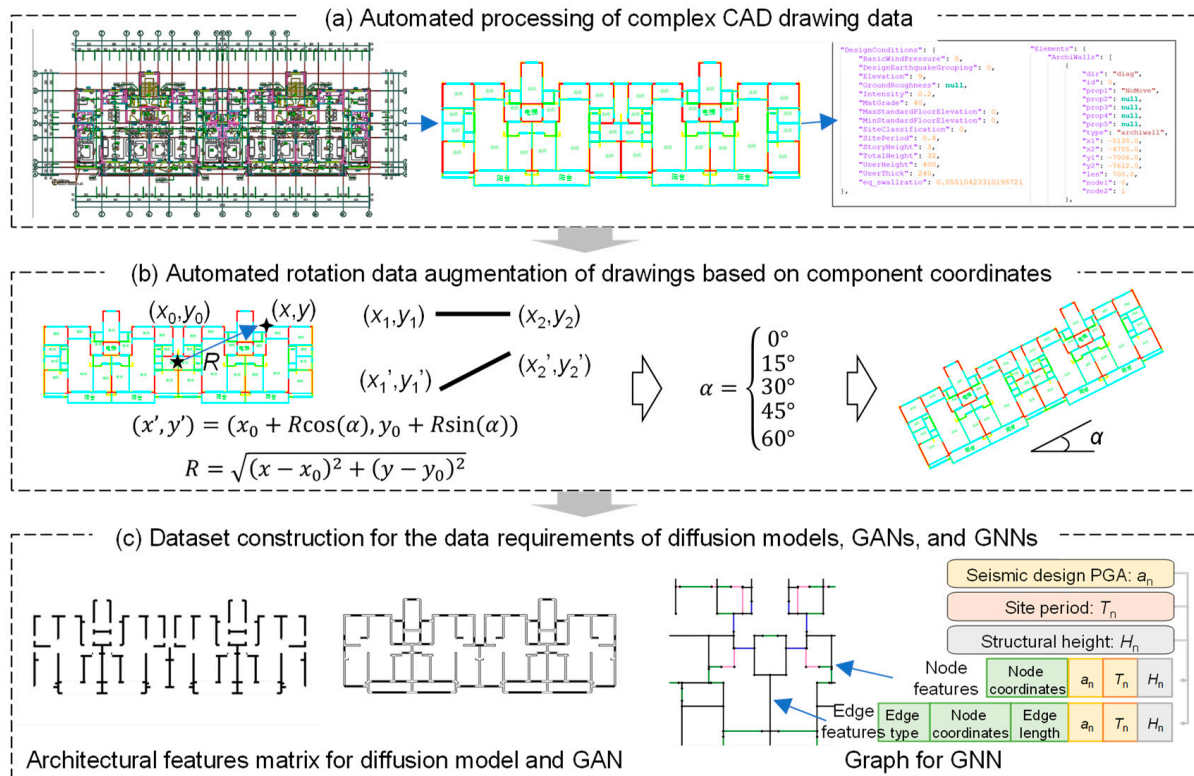


Figure 3. Data feature extraction, augmentation, and dataset creation method. (Note: some non-English characters in the CAD drawings for architectural layout design represent the names of building functional spaces.).

- (1) Automated processing of complex CAD drawing data (Figure 3a). Because the drawings originate from different design institutes, elements, layer naming, and other content within them differ, hindering the standardized batch processing of complex drawings. Therefore, a CAD-based data processing plugin is used to automatically extract the corresponding centerlines of components such as building walls, doors and windows, and shear walls, thereby obtaining the position coordinates of different components. Subsequently, the component centerlines are calibrated and adjusted to obtain high-quality component centerline drawings. Finally, the component centerlines are exported as structured standard data; this study uses the “key-value” JSON data format to store the standardized data.
- (2) Automated rotation data augmentation of drawings based on component coordinates (Figure 3b). Based on the extracted standardized data, the coordinates of all architectural and structural components are planarly rotated around the geometric center to obtain rotated architectural and structural design drawings. This method can effectively utilize design data for planar non-inclined building layouts to simulate planar inclined building layout designs that may be encountered in future designs. All components are, respectively, rotated by angles α of 0° , 15° , 30° , 45° , and 60° with the planar geometric center (x_0, y_0) as the reference point, thereby obtaining new data forms. These rotation angles are also rotational inclination angles commonly existing

in engineering design, which can better cover the design requirements for inclined components faced in actual designs.

- (3) Dataset construction for the data requirements of diffusion models, GANs, and GNNs (Figure 3c). For diffusion models and GANs, the input data is a three-dimensional tensor, formed by stacking different two-dimensional tensors along the channel dimension, in which each two-dimensional tensor records the planar position information of a type of component and structural design conditions (e.g., structural height, seismic design intensity, etc.) [4,27]. For GNNs, the input data is a graph with feature embeddings; first, building components are represented as edges, and component endpoints are represented as nodes. The edge feature vector includes component type, edge length, coordinates of the two end nodes, and the embedding of the structural design condition vector. The node feature vector includes node coordinates and other information [3].

The constructed image and graph data are organized and partitioned. For each generative AI algorithm, the total data volume is 1300 samples, of which 650 are original data with a 0° rotation angle, and the remaining 650 are data randomly rotated at different angles, resulting in a total of 1300 data samples. Subsequently, 20 data samples completely different from the training data are used for testing. After these 20 test data samples undergo rotation angle augmentation, a total of 100 test data samples are obtained.

Based on the dataset construction experience of this study, the following general guidelines for constructing augmented datasets for inclined structural component design are summarized:

- (1) Rotation angle selection. The selected rotation angles should cover the range of inclination angles commonly encountered in practical engineering design. In this study, angles of 0° , 15° , 30° , 45° , and 60° were selected, as these represent the most common inclination angles in Chinese residential building design.
- (2) Data standardization. Before rotation-based augmentation, CAD design data from different sources should be uniformly converted into standardized semi-structured data (e.g., JSON format), ensuring consistency in coordinate systems, component classification, and attribute information [26].
- (3) Balance between original and augmented data. The optimal ratio should be determined through validation-set evaluation. Excessive augmented data may interfere with the model's learning of original design features, whereas insufficient augmented data cannot effectively improve the model's design capability for inclined components.

2.2. Generative AI Model Training and Evaluation

The generative AI algorithms adopted in this study include diffusion models, GANs, and GNNs. The selection of diffusion models, GANs, and GNNs for comparative analysis is based on the following considerations. First, these three algorithms represent the most prominent generative AI paradigms currently applied to shear wall structural design, each embodying a distinct design approach: diffusion models are based on probabilistic denoising, GANs on adversarial training, and GNNs on graph topology learning. All three have been extensively studied and validated for orthogonal shear wall component design, with well-established model architectures and training methodologies. Second, these algorithms employ fundamentally different data representations—diffusion models and GANs operate on image-based feature tensors, while GNNs operate on graph-structured data. This diversity in data formats enables a comprehensive evaluation of how data augmentation affects different representational forms. Regarding other generative AI methods, transformer-based models for structural design are still in early exploratory stages, and no mature, directly applicable transformer model for shear wall layout design currently

exists. Reinforcement learning methods, while explored for structural optimization [17–19], have fundamentally different optimization objectives compared to generative AI design approaches, making direct comparison inappropriate.

These models are relatively cutting-edge intelligent design methods for shear wall structures. The model training and testing methods for these three algorithms will be introduced separately below.

- (1) The shear wall design method based on diffusion models was proposed by Gu et al. [4], as shown in Figure 4a. During model training, a U-Net network is constructed to predict Gaussian noise. Subsequently, by progressively adding Gaussian noise, a clear and complete shear wall structural design feature tensor (containing information such as shear walls, architectural walls, door and window layouts, and seismic design conditions) is gradually converted into Gaussian noise, and the U-Net acquires the capability to predict Gaussian noise during this process. During model testing, the reverse process of denoising is performed: a tensor containing only Gaussian noise is used, the trained U-Net predicts the noise, and this noise is progressively removed from the Gaussian noise tensor until a clear and accurate shear wall structural design is obtained.

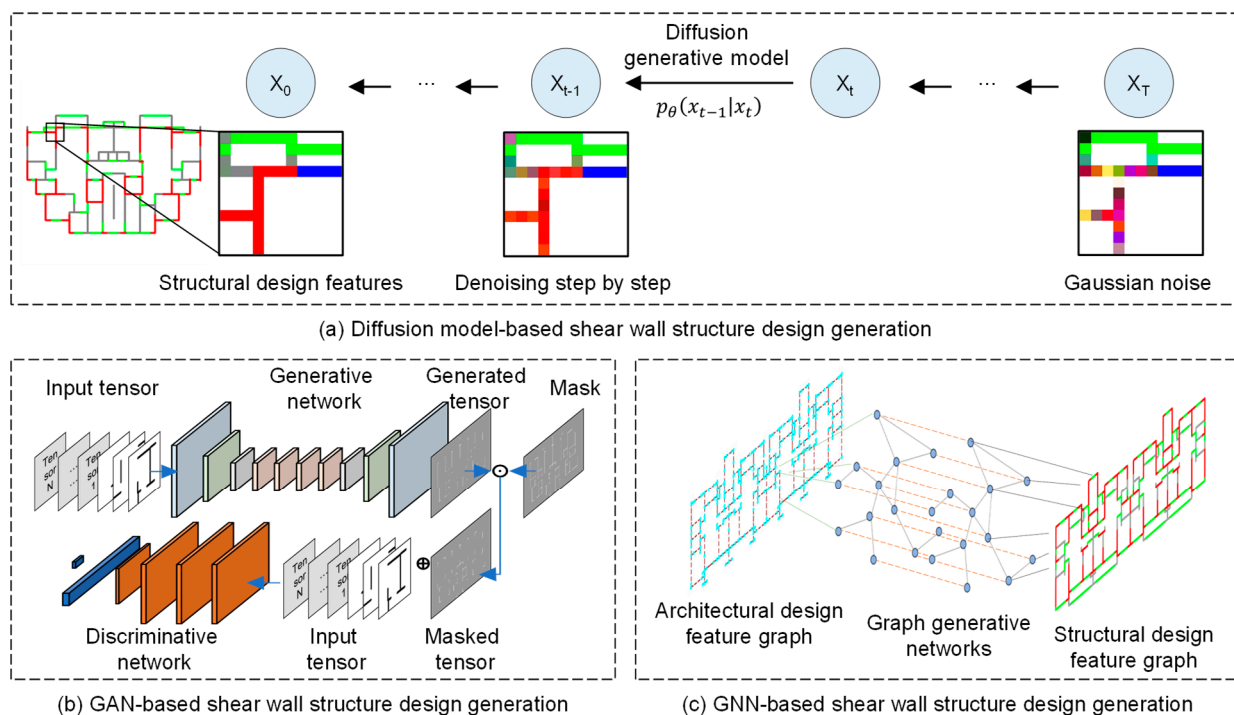


Figure 4. Design generation algorithm based on diffusion model, GAN, and GNN.

- (2) The GAN-based shear wall structural design method was proposed by Liao et al. [1] and improved by Han et al. [27], enabling GAN to learn architectural structural design feature tensors, as shown in Figure 4b. During model training, an architectural design feature tensor (containing information such as architectural walls, doors and windows, and seismic design conditions) is input, and a shear wall structural design feature tensor is output; the difference loss between the output feature tensor and the target design is calculated to guide model training. During model testing, the architectural design feature tensor to be designed is directly input into the trained GAN to generate the shear wall layout design feature tensor in one step.
- (3) The GNN-based shear wall design method was proposed by Zhao et al. [3], which involves representing architectural design and structural design using graphs, allowing

the GNN to learn the mapping generation rules from the architectural design graph to the structural design graph, as shown in Figure 4c. During model training, the architectural design graph (containing information such as architectural walls, doors and windows, seismic design conditions, etc.) is input, and the shear wall design graph (containing shear wall design coordinate information, with a topological relationship consistent with the input graph, but with different edge and node features) is output; the difference loss between the output graph and the target graph is calculated to guide model training. During model testing, the architectural design graph to be designed is input, and the shear wall layout design graph is generated in one step.

2.3. Intelligent Design of Inclined Shear Wall Layout Based on Generative AI

The process for intelligent design of planar inclined shear wall components, based on a trained generative AI model, is shown in Figure 2c. Architectural design CAD data containing inclined components undergoes data feature extraction to yield standardized architectural design data [26]. This data is then structured as input architectural design feature data for diffusion models, GANs, and GNN models, respectively. Subsequently, the architectural data is input into the trained generative AI model to directly generate corresponding design feature tensors or graphs that include inclined shear wall layouts. Finally, the shear wall structural feature tensors are converted into CAD drawing data, allowing users to make corresponding adjustments and perform subsequent structural modeling and calculations.

Among these, the vectorization method for designs involving inclined shear walls is not yet mature. Graph data, because it stores corresponding component coordinate information and topological relationships in its nodes and edges, is naturally vectorized data. Therefore, it does not require special post-processing, and the coordinates of the generated shear walls can be directly read out. In contrast, image data consists of pixelated coordinates, requiring the development of specific extraction methods to accurately back-calculate pixel coordinates into CAD vectorized coordinates. Therefore, this study further proposes a vectorization method for the inclined shear wall layout design tensor, as shown in Figure 5. It should be pointed out that the RGB color image of the shear wall layout design shown in Figure 5 is only for visualization purposes; the actual diffusion model and GAN output data are three-dimensional feature tensors, and the shear wall layout design is a specific channel of this tensor.

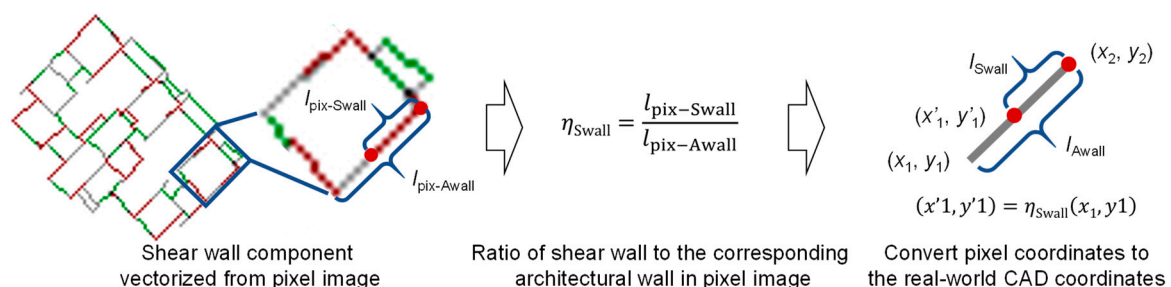


Figure 5. Vectorization method for inclined shear wall components.

First, according to the pixel coordinates of the building wall (known during data input), it is determined, pixel by pixel, whether the value of each pixel point within the building wall is a shear wall. This allows for obtaining, in a pixel coordinate system, the length proportion (η_{Swall}) and position coordinates of the shear wall components within the architectural wall. Subsequently, based on the real-world coordinates of the building wall, the shear wall component information is mapped from the pixel coordinate system to real-world coordinates, including one of its endpoints (which is the corresponding building

wall endpoint) and the shear wall length. Finally, by iterating through all building walls, the real-world CAD coordinates of all shear wall components can be completely extracted.

In addition, the vectorized extraction method proposed in this study for inclined shear wall components, based on the centerlines of building components after in-plane rotation, exhibits small and controllable error. First, because the orientation of the generated shear wall components is exactly consistent with that of the inclined building walls, no angular error is introduced during vectorization. Second, the main error source lies in the extracted component length. Statistical analysis shows that the mean pixel error is 2 pixels, corresponding to an actual coordinate error of approximately 200 mm.

3. Comparison of Design Results of Three Different Generative Intelligent Design Algorithms

For the intelligent design of shear wall layout, Liao et al. [2] and Han et al. [27] proposed corresponding GAN algorithms, Zhao et al. [3] proposed corresponding GNN algorithms, and Gu et al. [4] proposed corresponding diffusion model algorithms. For the layout problem of non-inclined shear wall components, these three types of algorithms each have their own advantages and disadvantages, and studies by Qin et al. [26], Wang et al. [28], among others, have compared the generation performance of different algorithms. However, for the inclined shear wall component layout design proposed in this study, a corresponding comparative analysis has not yet been conducted. In Section 2, after constructing an augmented dataset of inclined data by applying planar rotation to the training data, its data features and distribution underwent significant changes. The design performance of the three types of algorithms for such working conditions remains to be further analyzed and studied.

To evaluate the performance of different algorithms, a modified Intersection over Union (IoU) is adopted to assess AI-generated design. This evaluation method is highly efficient and suitable for simultaneously evaluating large datasets. The core of the IoU calculation is to compute the intersection and union lengths of AI-designed and engineer-designed shear walls. The corresponding calculation methods are shown in Equations (1)–(4), and this process is visualized in Figure 6. However, IoU calculation struggles to objectively reflect the influence of the shear wall ratio. When the shear wall ratio is relatively large, the IoU value tends to be high, whereas when the shear wall ratio is relatively small, the IoU value is usually lower, thereby reducing the objectivity of the IoU calculation results. Therefore, an S_{MIoU} evaluation metric, modified based on the shear wall ratio, was subsequently proposed, as shown in Equations (5) and (6).

$$M_{\text{struct}} = m_{i,j} = \begin{cases} 0, & \text{No structural elements} \\ 1, & \text{Structural elements} \end{cases} \quad (1)$$

$$M_{\text{struct}}^{\text{inter}} = M_{\text{struct}}^{\text{AI}} \odot M_{\text{struct}}^{\text{ENG}} \quad (2)$$

$$S_{\text{IoU}} = \eta_{\text{ratio}} \frac{L_{\text{inter}}}{L_{\text{union}}} \quad (3)$$

$$L_{\text{inter}} = \sum m_{i,j}^{\text{inter}}, L_{\text{union}} = \sum m_{i,j}^{\text{AI}} + \sum m_{i,j}^{\text{ENG}} - \sum m_{i,j}^{\text{inter}} \quad (4)$$

$$S_{\text{MIoU}} = \eta_{\text{ratio}} S_{\text{IoU}} \quad (5)$$

$$\eta_{\text{ratio}} = 1 - \frac{\left| \sum m_{i,j}^{\text{AI}} - \sum m_{i,j}^{\text{ENG}} \right|}{\sum m_{i,j}^{\text{ENG}}} \quad (6)$$

where, M_{struct} represents the structural layout position matrix (512×256), its elements mapping the spatial distribution of shear walls and beam members; $M_{\text{struct}}^{\text{AI}}$, $M_{\text{struct}}^{\text{ENG}}$ and

$M_{\text{struct}}^{\text{inter}}$ are Boolean matrices respectively representing the AI design, engineer design, and their spatial intersection, where the $\odot$ operator denotes the Hadamard product operation. S_{IoU} is the structural layout similarity IoU; L_{inter} and L_{union} , respectively, represent the effective structural member lengths in the intersection and union regions. S_{MIoU} is the modified structural layout similarity IoU, primarily to avoid the phenomenon of inflated IoU values resulting from an excessively high total length of structural members; η_{ratio} is the correction factor for the IoU calculation. $\sum m_{i,j}^{\text{AI}}$ and $\sum m_{i,j}^{\text{ENG}}$ respectively represent the total structural member lengths of the AI design and engineer design solutions. This correction mechanism can effectively eliminate bias in similarity assessment caused by differences in the total lengths of structural members.

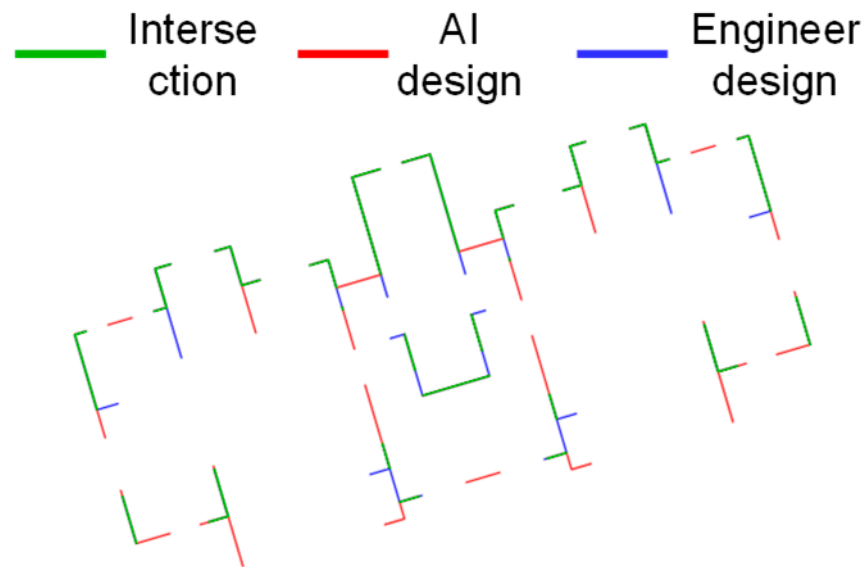


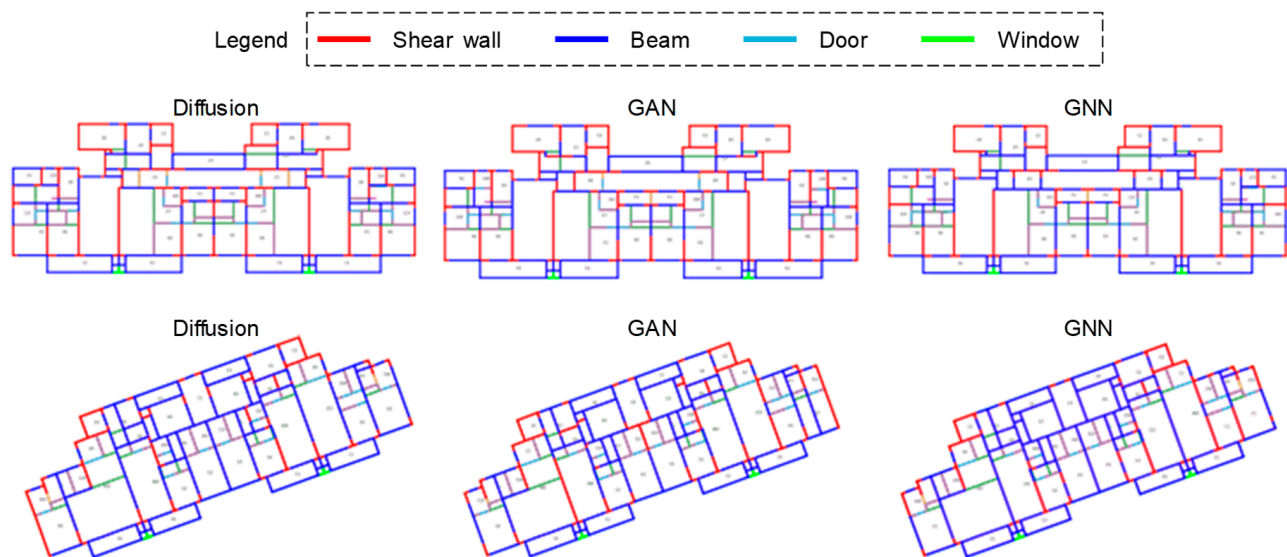
Figure 6. IoU calculation diagram.

The trained model is tested using the constructed test dataset, and quantitative evaluation is conducted using the modified IoU. The comparative analysis results are shown in Table 1, and the design results of some test cases are shown in Figure 7. The detailed analysis is as follows:

- (1) In a comparison of three generative AI algorithms, diffusion models performed best, GANs were second, and GNNs performed worst. The performance patterns of the three algorithms are largely consistent with existing research [28], but the specific scores show considerable differences, especially with a significant decrease in GNN scores. This indicates that using rotation angles for data augmentation on the training data did not further improve GNN model training. The main reason is that GNN models primarily learn structural topological relationships. Although this study rotated the component layout coordinates, it did not change the structural topology, causing the GNN model to learn different coordinate features for the same structural topology. This is akin to adding noise data to the structural design topology, which confused the GNN model's fitting and prediction process, ultimately leading to a decrease in design capability. In contrast, diffusion models and GANs learn image features. After planar rotation, they can be considered as entirely different images; therefore, the design performance of diffusion models and GANs showed greater improvement.

Table 1. Test results of different generative AI algorithms.

Test Data Rotation Angle	S_{MIoU}	Diffusion	GAN	GNN
0° (Original test data)	Mean value	0.515	0.438	0.259
	Standard deviation	0.1088	0.1056	0.1046
15°	Mean value	0.444	0.353	0.227
	Standard deviation	0.1399	0.1723	0.1003
30°	Mean value	0.460	0.358	0.229
	Standard deviation	0.1232	0.1508	0.1118
45°	Mean value	0.463	0.404	0.235
	Standard deviation	0.1187	0.1377	0.1116
60°	Mean value	0.452	0.376	0.230
	Standard deviation	0.1455	0.1475	0.1147

**Figure 7.** Design results of some test cases.

- (2) A comparison of test results for different rotation angles reveals that, once the test data is rotated, the design performance of the different algorithms all decreased to a certain extent. The primary reason is that the amount of rotated data in the training set is less than that of the original data. Furthermore, although this study aims to train the generative AI's capability for designing inclined shear walls, priority must also be given to ensuring the design performance for non-inclined shear walls; thus, the data volume for non-inclined shear wall designs is greater. Studies on the ratio of non-inclined data to inclined data also show that a 1:1 ratio of non-inclined data to inclined data achieves the best results.

Furthermore, to assess whether observed performance differences between models were statistically significant, Welch's independent two-sample *t*-tests (two-tailed) were performed for all pairwise model comparisons at each rotation angle. This non-parametric correction for unequal variances was chosen given the differing standard deviations observed across models. All tests used $n = 20$ per group, and significance was defined as $p < 0.05$. Effective degrees of freedom (*df*) were estimated using the Welch–Satterthwaite equation. No correction for multiple comparisons was applied, as all pairwise comparisons were pre-specified based on the experimental design.

Table 2 presents the results of pairwise Welch's *t*-tests for all model comparisons. The diffusion model significantly outperformed the GNN across all rotation conditions (all $p < 0.0001$), as did the GAN model (all $p \leq 0.008$). The diffusion model outperformed the

GAN at 0° ($t = 2.271$, $p = 0.029$) and 30° ($t = 2.343$, $p = 0.025$). Overall, the supplementary statistical analysis in Table 2 effectively substantiates the superiority of both the diffusion and GAN models over the baseline, while confirming that the diffusion model maintains a slight performance edge over the GAN in most scenarios.

Table 2. Pairwise Welch's independent two-sample t -test results ($n = 20$ per group).

Rotation	Comparison	Mean Diff (Δ)	t -Statistic	df	p -Value	Significance
0°	Diffusion vs. GAN	0.077	2.271	38	0.029	*
	Diffusion vs. GNN	0.256	7.587	38	<0.0001	****
	GAN vs. GNN	0.179	5.386	38	<0.0001	****
15°	Diffusion vs. GAN	0.091	1.834	36	0.075	ns
	Diffusion vs. GNN	0.217	5.638	34	<0.0001	****
	GAN vs. GNN	0.126	2.826	31	0.008	**
30°	Diffusion vs. GAN	0.102	2.343	37	0.025	*
	Diffusion vs. GNN	0.231	6.209	38	<0.0001	****
	GAN vs. GNN	0.129	3.073	35	0.004	**
45°	Diffusion vs. GAN	0.059	1.451	37	0.155	ns
	Diffusion vs. GNN	0.228	6.258	38	<0.0001	****
	GAN vs. GNN	0.169	4.263	36	<0.001	***
60°	Diffusion vs. GAN	0.076	1.640	38	0.109	ns
	Diffusion vs. GNN	0.222	5.359	36	<0.0001	****
	GAN vs. GNN	0.146	3.494	36	0.001	**

Note: ns: $p > 0.05$; *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$; ****: $p < 0.0001$.

4. Typical Case Studies

In addition to conducting testing and analysis of batch test data, this study also carried out a comparative analysis of intelligent design for typical design cases, including architectural design pre-processing, generative AI intelligent design, post-processing and CAD data generation, and automatic evaluation of structural mechanical performance. Through typical cases, the performance of the inclined shear wall structural design method proposed by this study was demonstrated, which can simultaneously generate intelligent designs with both inclined and non-inclined shear wall components.

It is important to note that the proposed method adopts a two-stage generate-verify workflow. The generative AI model first produces preliminary shear wall layout schemes, which are then verified against relevant design specifications using professional structural design software (PKPM V2.1.3). Design indices, including axial compression ratio, inter-story drift ratio, and shear-weight ratio, are checked, and schemes that fail to meet code requirements are revised or rejected. This workflow ensures that the final design output complies with relevant structural design codes.

4.1. Case Introduction

The building floor plan layout is shown in Figure 8. The building has an inverted triangular-shaped planar layout. The two units in the upper part are inclined arranged, and their building walls, doors, windows, and other components are all inclined arranged. The two units in the lower part are not inclined arranged. The building has a total of 18 natural stories. The seismic design intensity is 7 (0.15 g), and the site characteristic period is 0.4 s. This study primarily focuses on the scheme design of the building structure; therefore, only a single standard floor is used for the shear wall structural design.

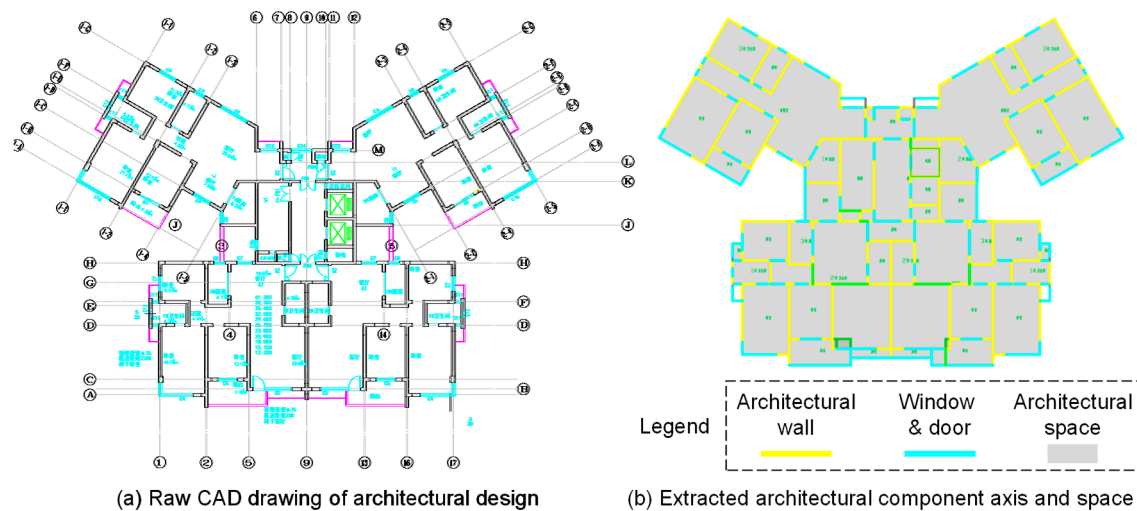


Figure 8. Architectural design drawing of typical case. (Note: The letters and numbers in the circles of subfigure (a) represent the grid axis numbers, and some non-English characters in the CAD drawings for architectural layout design represent the names of building functional spaces.).

4.2. Comparison of Three Design Algorithms

Based on the trained generative AI models, standardized building design information is input to carry out the shear wall-beam structural layout design. It should be noted that the beam layout design adopts a rule-based, hard-coded automatic beam layout design method [26]. The results of the shear wall-beam structural design are shown in Figure 9. It is evident that generative AI models trained with inclined shear wall component design data can all effectively generate the layout of shear wall-beam structural components.

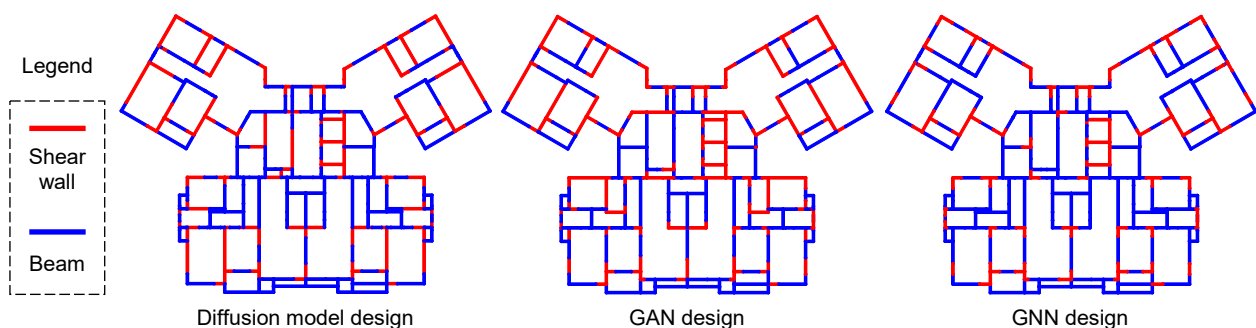


Figure 9. Shear wall structural layout design of a typical case.

- (1) From the perspective of the rationality of the planar layout, the design results of the diffusion model and GAN are both relatively reasonable. The placement positions of shear walls and the length dimensions of components are quite accurate, and the layout design at key corner positions can effectively resist the horizontal movement and torsional deformation response under seismic action. The GNN design results are poorer, with fewer shear wall positions and shorter shear wall lengths, leading to a weaker ability to resist seismic action, making it difficult to ensure the torsional stiffness and deformation capacity. Further, structural performance analysis is conducted to fully assess the quality of the structural design.
- (2) Using an automated modeling and analysis method developed based on the PKPM API, calculations are performed on the shear wall-beam structural scheme designs by generative AI. PKPM is one of the most used structural design software programs in China. The overall indicators of the structural calculations are shown in Table 3. Overall indicators are a key series of indicators that control the overall performance

of the structure. The indicators, shown in Table 3, must be fully met to fundamentally ensure the reasonableness of subsequent detailed and optimized design. Among these, the mechanical indicators of structures designed by diffusion models and GANs can both effectively meet code requirements and also possess a certain margin. In contrast, the GNN design is similar to the aforementioned judgment on planar layout design: GNN designs fewer shear walls, and its corresponding structural lateral stiffness is thus insufficient; this is directly reflected in the structure's stiffness-to-weight ratio and inter-story drift ratio under seismic action exceeding limits.

Table 3. Calculation results of PKPM mechanical indices for typical case designs.

Overall Indicators	PKPM Calculation Results			Design Code Limits
	Diffusion Model Design	GAN Design	GNN Design	
Vibration period in the x direction (s), T_x	1.5199	1.3459	1.8196	
Vibration period in the y direction (s), T_y	1.2768	1.1918	1.6895	
Torsional vibration period (s), T_t	1.1084	1.0428	1.3409	
Vibration period ratio (T_t/T_x)	0.7292	0.7748	0.7369	≤ 0.9
Minimal base shear/weight ratio in the x direction	0.0266	0.0278	0.0214	$\geq 2.4\%$
Minimal base shear/weight ratio in the y direction	0.0351	0.032	0.0264	$\geq 2.4\%$
Stiffness/weight ratio in the x direction	6.6075	9.4473	4.9962	> 1.40
Stiffness/weight ratio in the y direction	8.147	8.9136	4.505	> 1.40
Maximal inter-story drift angle ratio in the x direction	1/1189	1/1748	1/980	$< 1/1000$
Maximal inter-story drift angle ratio in the y direction	1/1593	1/1670	1/1138	$< 1/1000$
Maximal displacement ratio in the x direction	1.3566	1.3694	1.4682	< 1.50
Maximal displacement ratio in the y direction	1.3289	1.4047	1.3585	< 1.50
Maximal inter-story drift angle ratio in the x direction	1.3566	1.4051	1.4682	< 1.50
Maximal inter-story drift angle ratio in the y direction	1.331	1.4092	1.3604	< 1.50

Note: Indicators in bold font signify values that exceed the code limits.

Therefore, based on a comprehensive evaluation integrating empirical judgments of the planar layout and an analysis of PKPM calculation results, in the intelligent design of this case, the diffusion model and GAN design perform well. Specifically, the key mechanical indicators of the diffusion model effectively satisfy the code limits, and these indicators are not overly conservative. The diffusion model and GAN design results will be more conducive to subsequent design development and optimization.

5. Conclusions

Addressing the intelligent design demand for inclined components in shear wall structures, this study proposed a data augmentation dataset for planar rotated structural designs, trained models using generative AI algorithms, and established a vectorization method for pixel maps of inclined shear wall components, effectively achieving the intelligent generation of planar inclined and non-inclined shear wall structures. Furthermore, a detailed comparative analysis of three types of generative AI algorithms was conducted, demonstrating the extensibility of generative AI-driven intelligent design methods in addressing different design requirements.

- (1) A process was established for the intelligent design of the layout of planar inclined shear wall components, which includes planar rotation of design drawings of non-inclined components to simulate inclined component design scenarios, thereby enhancing the generative AI training dataset; training of generative AI algorithms; and vectorized extraction and efficient evaluation of pixel maps of inclined shear wall components.
- (2) A dataset augmentation method was proposed for inclined shear wall design: extract and correct the centerlines of building walls, doors and windows, shear walls, and other components from complex CAD drawings; output standardized, high-quality semi-structured JSON data of design information for building structural components;

automate the construction of inclined component data by rotating all component coordinates around the geometric center by 0° , 15° , 30° , 45° , and 60° ; and construct feature tensors, graphs, and other datasets for the training and learning needs of generative AI algorithms such as diffusion models, GANs, and GNNs.

- (3) For the shear wall structural design feature tensor output by diffusion models and GANs, a high-precision conversion method from pixel coordinates to real CAD coordinates was proposed: the two-dimensional tensor representing the shear wall design is extracted from the output shear wall design feature matrix. Based on the pixel coordinates of building components, the length ratio of the shear wall component to its host building wall component and the coordinates where the endpoints of the shear wall and building wall coincide are determined. Subsequently, the real CAD coordinates are calculated based on this ratio and endpoint coordinates, thereby achieving the vectorization of the shear wall feature tensor.
- (4) A comparative analysis and case studies of generative AI algorithms were conducted. The results indicate that diffusion models achieve the best design performance, GAN designs are second best, and GNN designs are weaker. The design performance of GNN models decreases quite significantly after data augmentation for inclined components, mainly because the structural topology remains unchanged while the coordinate features are altered, which is equivalent to GNNs learning more noise, thereby reducing their design capability. In contrast, the design capability of diffusion models and GANs for inclined shear wall components shows significant improvement.

In summary, the main theoretical contributions of this study are as follows: data augmentation can effectively improve the generalization ability of generative AI in building structural design; and the comparative performance of diffusion models, GANs, and GNNs on inclined component design tasks reveals how different generative paradigms respond to data augmentation. As a practical contribution, the proposed data augmentation and vectorized design workflow can be directly applied to real-world engineering, where this AI-driven approach shows great potential to advance sustainable construction by delivering material-efficient, seismically safe designs without over-conservatism, thereby reducing concrete and steel-related carbon emissions.

Limitations. Actual building structures containing inclined shear wall components require additional design considerations, including but not limited to differences in load-transfer paths, special torsional design requirements, and different structural systems such as mixed-use buildings and complex column-transfer structures. Therefore, the rotation-based data augmentation strategy cannot fully capture the underlying design logic. This limitation should be addressed in future work by incorporating more real structural design data. Moreover, the applicable boundary conditions of the proposed method should be clearly noted: (1) the maximum applicable inclination angle is 60° , and the method is not suitable for extremely irregular plan layouts; (2) the target structures are high-rise residential shear wall buildings with heights below 100 m.

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References

1. Liao, W.; Lu, X.; Fei, Y.; Gu, Y.; Huang, Y. Generative AI Design for Building Structures. *Autom. Constr.* **2024**, *157*, 105187. [CrossRef]
2. Liao, W.; Lu, X.; Huang, Y.; Zheng, Z.; Lin, Y. Automated Structural Design of Shear Wall Residential Buildings Using Generative Adversarial Networks. *Autom. Constr.* **2021**, *132*, 103931. [CrossRef]
3. Zhao, P.; Fei, Y.; Huang, Y.; Feng, Y.; Liao, W.; Lu, X. Design-Condition-Informed Shear Wall Layout Design Based on Graph Neural Networks. *Adv. Eng. Inform.* **2023**, *58*, 102190. [CrossRef]
4. Gu, Y.; Huang, Y.; Liao, W.; Lu, X. Intelligent Design of Shear Wall Layout Based on Diffusion Models. *Comput.-Aided Civ. Infrastruct. Eng.* **2024**, *39*, 3610–3625. [CrossRef]
5. Wang, L.; Liu, J.; Cheng, G.; Liu, E.; Chen, W. Constructing a Personalized AI Assistant for Shear Wall Layout Using Stable Diffusion. *arXiv* **2023**, arXiv:2305.10830. [CrossRef]
6. Zhou, Y.; Leng, H.; Meng, S.; Wu, H.; Zhang, Z. StructDiffusion: End-to-End Intelligent Shear Wall Structure Layout Generation and Analysis Using Diffusion Model. *Eng. Struct.* **2024**, *309*, 118068. [CrossRef]
7. He, Z.; Wang, Y.H.; Zhang, J. Generative AIBIM: An Automatic and Intelligent Structural Design Pipeline Integrating BIM and Generative AI. *Inf. Fusion* **2025**, *114*, 102654. [CrossRef]
8. Shim, J.; Moon, J.; Kim, H.; Hwang, E. FloorDiffusion: Diffusion Model-Based Conditional Floorplan Image Generation Method Using Parameter-Efficient Fine-Tuning and Image Inpainting. *J. Build. Eng.* **2024**, *95*, 110320. [CrossRef]
9. Fu, B.; Gao, Y.; Wang, W. Dual Generative Adversarial Networks for Automated Component Layout Design of Steel Frame-Brace Structures. *Autom. Constr.* **2023**, *146*, 104661. [CrossRef]
10. Fu, B.; Wang, W.; Gao, Y. Physical Rule-Guided Generative Adversarial Network for Automated Structural Layout Design of Steel Frame-Brace Structures. *J. Build. Eng.* **2024**, *86*, 108943. [CrossRef]
11. Tan, Z.; Qin, S.; Hu, K.; Liao, W.; Gao, Y.; Lu, X. Intelligent Generation and Optimization Method for the Retrofit Design of RC Frame Structures Using Buckling-Restrained Braces. *Earthq. Eng. Struct. Dyn.* **2025**, *54*, 530–547. [CrossRef]
12. Zhang, C.; Tao, M.; Wang, C.; Fan, J. End-to-End Generation of Structural Topology for Complex Architectural Layouts with Graph Neural Networks. *Comput.-Aided Civ. Infrastruct. Eng.* **2024**, *39*, 756–775. [CrossRef]
13. Leng, H.; Gao, Y.; Zhou, Y. ArchiDiffusion: A novel diffusion model connecting architectural layout generation from sketches to shear wall design. *J. Build. Eng.* **2024**, *95*, 110174. [CrossRef]
14. Zhang, T.; Lv, Y.; Liu, T.; Xu, W.; Wang, S.; Du, D.; Zhao, A. Inverse design of energy-dissipating steel plate walls based on self-supervised diffusion models. *Thin-Walled Struct.* **2025**, *210*, 113068. [CrossRef]
15. Santos, G.V.; Sotelino, E.D. Automated Structural Design of Industrial Plants: A Holistic Approach from GAN-Assisted Layout Generation to Early-Stage Cost Estimation. Available online: <https://ssrn.com/abstract=5800038> (accessed on 24 November 2025).
16. Fei, Y.; Lu, X.Z.; Liao, W.J.; Guan, H. Data enhancement for generative AI design of shear wall structures incorporating structural optimization and diffusion models. *Adv. Struct. Eng.* **2026**, *29*, 1369433225135361. [CrossRef]
17. Zhou, X.; Huang, X.; Liu, J.; Cheng, G.; Wang, L.; Hu, J.; Liu, P.; Chen, Y. Semi-Automatic Generation of Shear Wall Structural Models. *Structures* **2023**, *51*, 42–54. [CrossRef]
18. Lin, C.-H.; Fu, B.; Zhang, L.; Li, N.; Tong, G.-S. Intelligent Design of Steel–Concrete Composite Beams Based on Deep Reinforcement Learning. *Structures* **2024**, *70*, 107666. [CrossRef]
19. Wang, L.; Jiang, X.; Guo, W.; Lyu, F. Intelligent Design of Web-Stiffened Cold-Formed Steel Channel Beam Section Oriented by Load-Carrying Efficiency. *Structures* **2025**, *74*, 108571. [CrossRef]
20. Panagiotou, E.; Qian, H.; Marx, S.; Ntoutsis, E. Generative AI-augmented offshore jacket design: Integrated approach for mixed tabular data generation under scarcity and imbalance. *Autom. Constr.* **2025**, *176*, 106287. [CrossRef]
21. Hussain, H.; Payawal, J.M.G.; Kim, D. Data-driven prediction of cumulative plastic deformation for buckling restrained braces using generative adversarial networks (GAN) synthetic data augmentation. In *Proceedings of the First International Conference on Engineering Structures*; Springer Nature Singapore Pte Ltd.: Singapore, 2024.
22. Wang, Y.; Shi, Y.; Yang, T.Y. Structural performance warning based on computer intelligent monitoring and fractional-order multi-rate Kalman fusion method. *Fractal Fract.* **2026**, *10*, 186. [CrossRef]
23. World Green Building Council. *Bringing Embodied Carbon Upfront*; World Green Building Council: London, UK, 2019. Available online: <https://www.worldgbc.org/embodied-carbon> (accessed on 22 April 2026).

24. Huang, L.; Krigsvoll, G.; Johansen, F.; Liu, Y.; Zhang, X. Carbon emission of global construction sector. *Renew. Sustain. Energy Rev.* **2018**, *81*, 3046–3057. [[CrossRef](#)]
25. Bruneau, M.; Chang, S.E.; Eguchi, R.T.; Lee, G.C.; O'Rourke, T.D.; Reinhorn, A.M.; Shinozuka, M.; Tierney, K.; Wallace, W.A.; von Winterfeldt, D. A framework to quantitatively assess and enhance the seismic resilience of communities. *Earthq. Spectra* **2003**, *19*, 733–752. [[CrossRef](#)]
26. Qin, S.; Liao, W.; Huang, S.; Hu, K.; Tan, Z.; Gao, Y.; Lu, X. AIstructure-Copilot: Assistant for Generative AI-Driven Intelligent Design of Building Structures. *Smart Constr.* **2024**, *1*, 112311. [[CrossRef](#)]
27. Han, J.; Lu, X.; Gu, Y.; Liao, W.; Cai, Q.; Xue, H. Optimized Data Representation and Understanding Method for the Intelligent Design of Shear Wall Structures. *Eng. Struct.* **2024**, *315*, 118500. [[CrossRef](#)]
28. Wang, Z.; Yu, Y.; Chen, Y.; Liao, W.; Li, C.; Hu, K.; Tan, Z.; Lu, X. Expert Experience–Embedded Evaluation and Decision-Making Method for Intelligent Design of Shear Wall Structures. *J. Comput. Civ. Eng.* **2025**, *39*, 04024051. [[CrossRef](#)]

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