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Article

A Dynamic Reconstruction System for Historical Museum Spatial Narratives Based on Generative Adversarial Networks (GANs)—A Semantic Coherence Protection Mechanism for Dispersed Cultural Relics

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Abstract: Historical museums offer dual insights into the revitalisation and creative dissemination of intangible cultural heritage, dynamically reconstructing historical memory through spatial narratives and fostering contemporary dialogue through the activation of historical spatial narratives. This article takes the dynamic reconstruction mechanism of spatial narratives in historical museums as its starting point, analysing the multi-layered narrative design of historical museums based on narrative theory and spatial narrative concepts, and proposing a semantic contextual reconstruction method for spatial narratives in historical museums. Based on this, a visual symbol extraction method for historical museums is constructed using filters and CNN, with TF-IDF algorithms to extract semantic information from visual symbols, and FCM clustering algorithms to perform keyword clustering of cultural relic space semantics. Self-attention mechanisms, spectral normalisation, and gradient normalisation are introduced to optimise GAN, constructing an improved GAN-based visual symbol translation model for historical museums. Taking the Beijing History Museum as the research object, data analysis was conducted on the model's performance and spatial narrative expression. The semantic space of historical museum artefacts was primarily divided into nine clustering labels, and the overall performance of the visual symbol translation model was satisfactory. After implementing the spatial narrative optimisation strategy, the participants' experience scores increased by 61.69%, and over 80% of the audience expressed approval for the historical museum's spatial narrative update mechanism. Therefore, by dynamically reconstructing the spatial narrative of historical museums, discrete artefacts can be given a more coherent preservation approach, thereby enhancing audience experience in historical museums and creating a more vibrant cultural emblem.

Keywords: TF-IDF algorithm; FCM clustering algorithm; self-attention mechanism; GAN; historical museum; spatial narrative

1. Introduction

Since the 20th century, with the joint development of narratology and architecture, scholars have gradually recognised the narrative function of architecture, raising issues such as “event discourse” and “constructing spatial and cultural meaning within architecture” [1-2]. Academic research and discussions on the narrative aspects of different types of architecture have been relatively broad, lacking specific narrative studies focused on particular types of architecture. As a type of architecture that carries historical and cultural significance, museums not only house tangible cultural heritage but also preserve humanity's memories over the course of history. The impulse to narrate is an impulse to seek lost time, and the essence of narration lies in the solidification and preservation of mysterious, fleeting time [3-5]. As a link in the historical timeline, museums bear significant responsibilities for spiritual development.

Historical museums, as an important form of museum, primarily exhibit historical artefacts and possess the ability to narrate history with the highest authority and authenticity [6-8]. Additionally, they guide society in observing and reflecting on historical artefacts, thereby shaping people's perceptions of historical art [9].

Narrative can present museum collections in the form of dormant memories and make historical stories tangible and accessible through storytelling [10]. Narrativity is an inherent ability of other art forms such as text, images, film, and theatre, possessing unique narrative structures and forms, as if these media were specifically created for the purpose of storytelling [11-12]. For architecture, after being liberated from decorativeism, it embraced functionalism, gradually expanding the functions of space. This has led to an inevitable interaction between architectural space and people, much like how a city's fabric silently reveals its deep historical heritage. This narrative ability is subtle, and its narrative structure and form have developed under the influence and permeation of other art forms [13-16].

Li et al. [17] used big data to explore the spatial distribution of cultural relics in museums, categorising them into three forms: category clustering, dynasty clustering, and regional clustering. In terms of time, the distribution exhibits continuity, discontinuity, and similarity, while in terms of space, it exhibits clustering, migration, and similarity. Currently, over 50% of global museum collections are in a dispersed state due to factors such as loans, exhibitions, repairs, disasters, and political instability. The most prominent phenomenon is the scattering of artefact fragments across different museums in multiple countries, leading to a loss of semantic coherence and impaired narrative coherence [18-19]. Additionally, differing display rules for series of artefacts across museums further impact narrative effectiveness. To address this, Miao et al. [20] revealed under spatial design narrative strategies that rational spatial layout, narrative coherence, and multi-sensory interactive experiences can enhance audience attention and alleviate museum visitor fatigue. Firliani et al. [21] introduced the Kota Air Museum in Surabaya, which uses water as a spatial language medium to narrate historical memory and construct spatial sensory experiences for visitors. Among existing technologies, 3D reconstruction technology is commonly used for the display and preservation of heritage artefacts. Nie et al. [22] designed 12 narrative elements based on narratology and utilised 3D reconstruction technology to create a narrative interaction framework for artefacts in museums, forming a 3D narrative model. Brumana et al. [23] integrated multi-temporal, multi-scale mapping and geospatial data, along with technologies such as panoramic photos, 360° videos, and 3D models, to achieve narrative and immersive experiences in a virtual museum. Chen et al. [24] designed a museum spatial layout framework in a virtual reality environment, incorporating narrative elements across three levels: collections, exhibition halls, and the museum itself. This framework was used to create a system named VirtuNarrator, enabling visitors to personalise their narrative themes, select collections, and arrange exhibition halls.

Generative Adversarial Networks (GANs) are a machine learning technique that uses two adversarial neural network models, namely generators and discriminators, to train generative models and infer generated samples. They can be used for various generative tasks, such as image generation, audio generation, and text generation [25-26]. Atairu [27] employed GAN technology to design the “Igoun-Style GAN Series” project, reinterpreting the bronze artefacts of the Benin Kingdom. Nogales et al. [28] utilised GAN technology to capture the stylistic features of the original image, extracting and supplementing missing elements to restore the artificial landscape images of Greek temple archaeological sites. Chen and Lyu [29] introduced self-attention modules into deep convolutional GANs to generate design diagrams for virtual exhibition halls and combined these diagrams to construct three-dimensional virtual exhibition halls with interactive experiences. Garozzo et al. [30] generated realistic classical order images using GANs based on semantic ontology domain representations, which aids in the understanding of cultural heritage scenes.

As a bastion of cultural heritage, historical museums serve as venues for disseminating knowledge and play a pivotal role in the interaction and reinterpretation of cultural emotions. This article, based on narrative theory and spatial narrative concepts, analyses the multi-layered narrative design of historical museum exhibitions and explores strategies for reconstructing the semantic context of spatial narratives in historical museums. To better integrate disparate artefacts, this study introduces CNN and filters to symbolically represent artefacts, uses the TF-IDF algorithm to extract their spatial semantic features, and combines the FCM algorithm for keyword clustering. Based on this, the original GAN is improved using self-attention mechanisms, spectral normalisation, and gradient normalisation to further enhance the translation effect of visual symbols in historical museums. The effectiveness of the translation model is validated through simulation, and the spatial narrative performance of historical museums is analysed, aiming to further enhance the coherence of historical museums in preserving scattered artefacts and thereby improving their cultural education effects.

2. Dynamic Reconstruction of Spatial Narratives in History Museums

The spatial narrative form of the history museum breaks the public's fixed perception of traditional cultural relics and subverts the dull experience of stereotypical exhibition modes, allowing the serious and weighty history of cultural relics to break out of its rigid historical setting and become familiar legends. This interpretation also redefines the function and social value of history museums, raising the public's expectations and demands for the current exhibitions and experiences offered by history museums.

2.1. Narrative Construction in Museum Exhibitions

2.1.1. Basic manifestations of narrative theory

Narrative theory is rooted in disciplines such as anthropology and literary theory, with the central premise that people tend to adopt narrative modes when cognising and describing the world, relying on the construction of plots, the description of events, and the creation of characters to give meaning and structure to experiences. Narrative is not merely a means of information transmission but also a medium for understanding the world, constructing identity, and fostering cultural recognition. In the exhibition practices of historical museums, this theory advocates the use of specific narrative frameworks to present exhibition content, enabling viewers to engage with the exhibition on three levels: sensory experience, rational understanding, and emotional resonance [31].

In narrative theory, core elements encompass story plot structure, temporal and spatial framework arrangement, and character development. Specifically, story plot structure and temporal and spatial framework arrangement form the basic framework of narrative. Through the orderly arrangement of these elements, historical museums can create a unified historical or cultural narrative, enabling visitors to construct a complete understanding on both visual and emotional levels. In the narrative process, characters typically symbolise various historical individuals, cultural symbols, or social units. Their behavioural and emotional development trajectories serve as important channels for visitors to interpret the exhibition's content and experience history and culture.

2.1.2. Characteristics of the concept of spatial narrative

Narrative, or “storytelling,” is a fundamental form of human expression that deeply reflects human cognition and ways of thinking. Spatial narrative draws inspiration from literary narrative thinking, leveraging the unique medium of three-dimensional space to seamlessly integrate exhibition content through the logical framework of “event-space-time.” This approach endows the space with “recognisability” and “intentionality,” enabling it to convey exhibition content to audiences in a fluid manner while deeply interpreting its underlying cultural essence.

Spatial narrative is a creative way of thinking that allows visitors to become storytellers within the exhibition space of a historical museum, serving as a bridge between the viewer's perception and the physical space. Through multi-sensory experiences such as visual and tactile stimuli, spatial narrative can evoke emotional resonance in visitors, thereby achieving the goal of precisely conveying the theme of the spatial exhibition to the audience. This concept transcends the temporal limitations of traditional narrative, achieving a multi-layered narrative that coexists in both time and space. It introduces a new expressive language for the dynamic reconstruction of spatial narrative design in historical museums, significantly enriching the layers and hues of spatial expression, and opening up a broader creative landscape for optimising spatial narrative methods in historical museums.

2.1.3. Multifaceted composite narrative design

The essence of narrative lies in recounting the sequence of events of a story. It is a fundamental human means of expression and communication, as well as an effective approach to interpreting and reconstructing the human world. If narrative is likened to “telling a story,” then narrative design is the technique of storytelling—that is, “how to tell it.” Every story in a history museum has its own unique characteristics, which determine its narrative design and the way it interacts with the audience. Each story, due to its distinct narrative design, varies in content and intensity of expression.

Audiences' diverse preferences regarding the content and form of historical museums have already manifested a strong trend toward autonomy in their behaviour. Historical museums exhibit narrative characteristics that are entirely distinct from those of novels, films, and plays, necessitating the development of a unique narrative design system. Precisely because historical museums, as public media, must cater to the diverse needs of audiences and provide multi-sensory experiences—possibilities that other narrative systems cannot achieve—they present a composite form within their spaces. Collections, as the primary medium, are naturally a very important part of historical museums. Traditional approaches have overly relied on "objects" to generate narratives through contextualisation, resulting in a relatively non-explicit design that requires audiences to interpret the narrative indirectly, making effective communication challenging. How to enable audiences to gain richer information and narratives based on "objects" and establish interactive relationships with them becomes the key. Through audiences' reading and listening to the symbolic system, observing and browsing the visual system, and experiencing the interactive system within the space, the narrative design system of historical museums is established, thereby forming the uniqueness of historical museum narratives.

2.2. Reconstructing Narrative Strategies for History Museums

2.2.1. Semantic Reconstruction of Spatial Narratives

The approach to transforming visual symbols into spatial narrative semantics in historical museums is a cross-media creative process involving "encoding-decoding-mapping-reconstruction." The specific implementation process is as follows:

First, extract the core semantics of historical artefact visual symbols, separate the signifier and signified of historical artefact visual symbols, establish a correspondence between the two, and transform them into convertible spatial elements.

Secondly, we need to explore the themes, regional cultures, folk customs, and narrative logic of historical relics, and sort out the corresponding relationships between these implicit symbols and cultural connotations.

Thirdly, establish a mapping relationship between visual symbols and spatial elements. In other words, transform the symbolic meanings extracted and translated from the visual elements of historical artefacts into the narrative language of thematic spatial design, and translate and map them into spatial structure, decorative interfaces, scene creation, and multi-sensory experiences.

Finally, the translated element symbols are used to encode the spatial narrative. The spatial flow can be organised by emulating the dramatic structure of "exposition, development, turning point, and resolution," and different visual symbols can be juxtaposed. For example, new materials and traditional elements can form a cross-temporal dialogue, allowing visitors to interact with the space through modern digital technology, thereby enabling both people and space to participate in the construction of the narrative [32].

2.2.2. Reconstructing the Context of History Museums

The theory of spatial production reveals the essence of space as a carrier of social relations and ideology, while historical museums are carriers of existing visible intangible culture. Through the display of artefacts and the narrative reconstruction of historical artefacts, historical museums engage in production and reproduction in material space, constructing historical memory and transmitting cultural values.

"Spatial Triad Theory" provides a three-dimensional perspective for dynamically reconstructing the contextual narrative of historical museum spaces. Spatial practice refers to the physical form and usage of material spaces, including the design of historical museum buildings, artefacts, and visitor flow. Spatial representation refers to the ideological space constructed through planning and symbolic structures by power entities. For example, historical museums convey the narrative of "cultural integration" through textual labels and the arrangement of exhibits. Representational space refers to the emotional and cognitive space generated by users (visitors) during their experience, such as the personalised historical imagination formed by visitors during VR tours. These three elements dynamically interact, collectively shaping the social significance of spatial narrative in historical museums.

The narrative exhibition practice of historical museums is essentially a process of spatial production. Through the reshaping of physical spaces, the translation of cultural symbols, and the intervention of technological media, it achieves the reproduction of historical culture and the implicit dissemination of power discourse, thereby transforming historical culture from the semantic context of artefacts to a narrative space.

3. Extraction and translation of visual symbols from historical museums

The visual symbols of intangible cultural heritage in historical museums encompass both external manifestations and internal meanings. External manifestations are reflected in the production process and outcomes, existing in the form of physical space, while internal meanings reflect second-space elements such as human will, culture, spirit, and philosophy. Based on this, this paper extracts the semantic features of intangible cultural heritage artifacts in historical museums and introduces an improved GAN model to construct an intangible cultural heritage reconstruction and translation model. The purpose is to better assist audiences in immersively experiencing the development of artifacts during exhibitions and further enhance the spatial narrative capabilities of historical museums.

3.1. Extraction of visual symbols from historical museums

3.1.1. Methods for extracting visual symbols

The semantic information of an image can be represented by certain elements or visual feature symbols. Typically, 2D convolutions use hundreds of filters and graph convolutions use hundreds of "hidden nodes" to detect all possible concepts, but this requires a large amount of computation, which is not conducive to the practical application of the model. To represent image information using only a small number of visual concept symbols, this paper designs a visual symbolisation module for historical museum artefacts based on existing related research, converting the visual feature map of the artefacts into a set of compact feature symbols.

The input feature map is defined as $X \in R^{(H \times W \times C)}$ (H, W and C represent the height, width, and number of channels of the feature map, respectively), and the visual symbol is defined as $T \in R^{L \times C}$ (L is the number of semantic symbols, and $L \ll H \times C$). This section investigates two different symbolisation methods, namely filter symbolisation and cyclic symbolisation.

(1) Filter symbolisation. For feature map X , each pixel $X_p \in \mathbb{R}^c$ is mapped to a semantic group (L semantic groups in total) using pointwise convolution, and then spatial pooling is performed on each semantic group to obtain spatial attention A . Finally A , the feature map X is multiplied back, and the weighted average of the pixels in X is calculated to obtain the feature symbol T^k of layer k , represented as:

$$T^k = softmaxx_{HW}(XW_A)^T \tag{1}$$

Among them, $W_A \in \mathbb{R}^{C \times L}$ are learnable weights used to calculate semantic groups from feature map X (the output of the last convolutional layer), which are then converted into spatial attention based on SoftMax operations.

(2) Recursive symbolisation. Due to the limitations of filter symbolisation, recursive symbolisation was proposed based on existing research, i.e., using the feature symbols of the previous layer as weights to guide the symbolisation of this layer. Then:

$$W_A = T^{k-1} W_{T \to R} \tag{2}$$

$$T^k = softmaxx_{HW}(XW_R)^T X \tag{3}$$

Where T^{k-1} represents the feature symbol of the $k-1$ layer and T^k represents the feature symbol of the k layer. Based on the feature symbols of the previous layer, the model can automatically learn the weights, thereby guiding the generation of feature symbols for this layer. Since the feature symbols of the previous layer are needed as guidance, cyclic symbolisation is actually only used from the second layer onwards.

After symbolising the high-level semantics of images, it is necessary to construct a relationship model between these feature symbols. This paper uses the Transformer encoder structure to construct the relationship model, based on the input to construct the weight model of feature symbols, and calculates through key values and queries. It supports visual feature symbols with variable meanings, which can cover more possible concepts with fewer symbols. The calculation process can be represented as:

$$T_{out}^{'} = Norm\{T_{in} + softmax_L[(T_{in}K)(T_{in}Q)^T T_{in}]\} \tag{4}$$

$$T_{out} = Norm[T_{out}^{'} + ReLU(T_{out}^{'} F_1) F_2] \tag{5}$$

Among them, $T_{in}, T_{out}^{'}, T_{out}$ and are feature symbols, while $(T_{in}K)(T_{in}Q)^T \in \mathbb{R}^{L \times L}$, F_1 , and F_2 are the weights of the fully connected layer.

Since distortion alters the underlying features of an image-for example, JPEG compression changes the texture structure of an image, Gaussian white noise alters the overall colour of an image, and the symbolisation process may affect the structural features of an image-Therefore, this paper constructs a cultural relic underlying image feature extraction network based on CNN to extract the underlying visual symbolic information of cultural relic images. It primarily includes five convolutional layers, with kernel sizes of 9×9, 6×6, and 3×3, all with a stride of 1×1, and ReLU is selected as the activation function to ensure the integrity of the extracted visual symbolic information of cultural relics.

3.1.2. Spatial semantic keyword clustering

When reconstructing spatial narratives in historical museums, changes in the spatial narrative semantics of different artefacts in the museum also affect the design of dynamic reconstruction. Based on this, this paper extracts spatial semantic keywords from the semantic descriptions of different artefacts in historical museums, with the aim of providing support for optimising the spatial narrative effects of historical museums.

This paper first uses the TF-IDF algorithm to count how often the spatial semantics of historical museum artefacts appear, to analyse how important this semantics is to historical museums. This algorithm is made up of two parts: the TF algorithm and the IDF algorithm. The TF algorithm counts how many times a word appears in a document to assess how well it expresses the document. The more times a word appears in a document, the better it expresses the document. Here's how it's calculated:

$$TF_{ij} = \frac{n_{ij}}{\sum_{k}^{n} k_j} \tag{6}$$

In the formula, the numerator n_i represents the frequency of occurrence of word i in document j, and $\sum_{i}^{n} k_j$ represents the sum of the number of occurrences of each word in document s.

The IDF algorithm calculates the IDF value of a word by counting the number of documents in a document collection that contain that word. The basic idea is that if there are fewer documents in the collection that contain the word, the word will be more effective in distinguishing between documents. The calculation method is as follows:

$$IDF_i = \lg\left(\frac{|D|}{1+|D_i|}\right) \tag{7}$$

In the formula, $|D|$ is the total number of documents in the document collection, and $|D_i|$ is the number of documents in which word i appears.

The TF-IDF algorithm is a combination of the TF algorithm and the IDF algorithm. This algorithm considers both the frequency of words appearing in a document and the ability of words to distinguish between documents, thereby better highlighting the importance of words in a given text. The calculation method is as follows:

$$TF_{IDF(ij)} = TF_{ij} \times IDF_i = \frac{n_{ij}}{\sum_{k}^{n} k_j} \times \lg\left(\frac{|D|}{1+|D_i|}\right) \tag{8}$$

In the formula, $TF_{IDF(ij)}$ represents the TF-IDF value of word i in the document.

Clustering algorithms are a commonly used analytical method in data mining tasks, capable of uncovering deeper insights hidden within databases. The core principle of clustering algorithms is that similar items tend to cluster together, grouping elements with identical attributes into the same category and separating those with distinct attributes into different categories. Clustering analysis can be used as a standalone process to identify the intrinsic distribution structure of data, or as a preliminary step for other tasks, where data is first clustered and then models are trained separately for each cluster [33].

The ideal result of clustering is that clusters are tightly grouped within each other and far apart from each other. To achieve this, the between-cluster-intra-cluster percentage (BWP) metric is used as the optimal clustering objective. This metric is dimensionless and comprehensively considers the minimisation of intra-cluster distance and the maximisation of inter-cluster distance.

Order w For clustering space, assuming that n text semantic features $\hat{x}'$ are clustered into l categories, the BWP index of the i semantic feature sample $\hat{x}'$ in the o category is defined as:

$$\begin{cases} L_{BWP} = (v(o,i) - q(o,i)) / (v(o,i) + q(o,i)) \\ v(o,i) = \sum_{1 \le a \le i, a=o} \left(\frac{1}{n_a} \sum_{p=1}^{n_a} \| x_p^{(a)} - x_i^{(o)} \|^2 \right) \\ q(o,i) = \frac{1}{n_o - 1} \sum_{q-1, q \ne i}^{n_o} \| x_q^{(o)} - x_i^{(o)} \|^2 \end{cases} \tag{9}$$

In the formula, $v(o,i), q(o,i)$ represents the minimum inter-class distance and intra-class distance of the i semantic feature sample in the o class, $\| \cdot \|^2$ represents the squared Euclidean distance, $x_i^{(o)}$ and $x_p^{(a)}$ represent the i / p sample in the o / a class, where a and o are class labels. n_a denotes the number of samples in the a class, $x_q^{(o)}$ denotes the q semantic feature sample of the o class, and $q \ne i$ and n_o denote the number of semantic feature samples in the o class.

The larger the BWP indicator value, the better the clustering effect of individual semantic feature samples. Therefore, the K-means algorithm is combined with this indicator. Based on a given clustering number search range $[l_{\min}, l_{\max}]$, the average BWP indicator value of all semantic feature samples in the entire text semantic features $L_{avgBMP}(l)$ can be calculated to determine the optimal clustering number l_{opt}. The formula is:

$$\begin{cases} L_{avgBMP}(l) = \frac{1}{n} \sum_{o=1}^{l} \sum_{i=1}^{n_o} (\hat{x}_o', \hat{x}_i') \\ l_{opt} = \arg\max_{2 \le l \le n} \{ L_{avgBMP}(l) \} \end{cases} \tag{10}$$

After determining the optimal number of clusters as l_{opt}, the FCM clustering algorithm was used in combination with the optimal number of clusters to further optimise the clustering results. This algorithm divided the n multimodal deep text semantic features $\hat{x}' = \{x_1, x_2, ..., x_n\}$ into c fuzzy groups and obtained the clustering centre c_i of fuzzy group i to minimise the dissimilarity index of the objective function. The objective function formula is:

$$\begin{cases} K(O, c_1, c_2, ..., c_c) = \sum_{i=1}^{c} K_i = \sum_{i=1}^{c} \sum_{o}^{n} o_{io}^{y} d_{iq}^{2} \\ O \in \sum_{i=1}^{c} o_{io} = 1, \forall = 1, 2, ..., n \end{cases} \tag{11}$$

In the formula, $d_{iq} = \| c_i - x_q \|$ represents the Euclidean distance between the i cluster centre and the q feature sample point, O represents the membership degree matrix, o_{io} represents the membership degree of the i cluster centre in class o, and $y \in [1, \infty)$ represents the weighting index.

In order to obtain the optimal fuzzy clustering partition, based on the given optimal number of clusters, calculate $\min\{K(O, c_1, c_2, \cdots, c_c)\}$, with constraint conditions $v_o (o = 1, 2, \cdots, n)$, and the new objective function is:

$$\begin{aligned} \bar{K}(O, c_1, c_2, ..., c_c, v_1, v_2, ..., v_n) = K(O, c_1, c_2, ..., c_c) \\ + \sum_{o=1}^{n} v_o \left(\sum_{o=1}^{n} o_{io} - 1 \right) \end{aligned} \tag{12}$$

Finally, according to the above formula, the c cluster centres are calculated as follows:

$$c_i = \left(\sum_{o=1}^{n} o_{io}^{a} x_i \right) / \sum_{o=1}^{n} o_{io}^{a} \tag{13}$$

If the result of the objective function (12) is less than a certain threshold, the algorithm is terminated. Otherwise, the new O matrix is calculated using the following equation, and the iteration continues using equation (13) until the termination condition is met. This determines the classification of each text semantic feature, clusters similar feature points into a group, and forms multiple clusters.

3.2. Translation of Visual Symbols for History Museums

3.2.1. Mechanism of Generative Adversarial Networks

Generative adversarial networks (GANs) consist of a generator and a discriminator. The generator creates new data, while the discriminator determines whether the data is real. The two compete against each other during training, with the generator attempting to generate more realistic data samples to deceive the discriminator, while the discriminator tries to identify the differences between the data generated by the generator and real data. This adversarial process enables the generator to gradually improve the realism and quality of the data it generates.

The optimisation objective function of GAN is to make the samples generated by the generator more realistic by minimising the JS divergence between the generator and the discriminator [34]. Specifically, assuming that our generator is G, the discriminator is D, the input noise is z, and the real data is x, the objective function can be expressed as:

$$\min_G \max_D V(D,G) = \min_G \max_D [E_{x\sim p_{data}(x)} \log D(x) + D(G(z))] \tag{14}$$

In the equation, $E_{x\sim p_{data}(x)}$ represents the mathematical expectation of random variable x under the true data distribution, $G(z)$ represents the fake data generated in the generator based on z, $D(x)$ represents the result judged by the discriminator on the true data x, and $D(G(z))$ represents the result judged by the discriminator on the fake data $G(z)$. In the equation, first fix the generator G and maximise the loss from the discriminator's D perspective. Then fix D and minimise the loss from the generator's G perspective. This allows the discriminator and generator to achieve adversarial learning while sharing the loss.

3.2.2. Improving GAN Symbol Translation

(1) Self-attention mechanism

In the self-attention mechanism (SA), key-value pairs have a significant impact on attention. After each element in the input information sequence undergoes query, key-value mapping, the self-attention mechanism calculation formula can be expressed as:

$$\begin{aligned} att(Key, Value, Query) &= \sum_{i=1}^{N} \frac{\exp(s(k_i, q))}{\sum_j \exp(s(k_j, q))} v_i \\ &= soft\max\left(\frac{Query * Key^T}{\sqrt{d_k}}\right) Value \end{aligned} \tag{15}$$

In the formula, Key, Value, and Query represent the product of the input matrix X, which is essentially a linear transformation of X. The Softmax function transforms the input into a probability distribution, stabilising the output value range between 0 and 1 and reducing the influence of the bias term.

In the computational process of the self-attention mechanism, the implementation primarily relies on the linear transformation of three weight matrices. After initialising the weights, the query value Q, key value K, and value vector V are first calculated. The attention score for the first input is then computed, followed by normalisation processing using the SoftMax function in conjunction with the attention scores. Each SoftMax function result is then multiplied by the corresponding V value, yielding three weighted V values. Finally, all weighted V values are summed element-wise to produce the final output. The introduction of the self-attention mechanism enables the acquisition of dense global contextual information, allowing the model to no longer rely on the combination of convolutional layers and pooling layers for feature extraction and receptive field expansion. Instead, it directly establishes dependencies between input pixels using the self-attention mechanism.

(2) Spectrum normalisation

Conventional generative adversarial networks suffer from instability during training. Lipschitz constraints limit the maximum gradient of a function, defined as:

$$f(x_2) - f(x_1) \le M(x_2 - x_1) \tag{16}$$

In the formula, M is a constant, x_1 and x_2 are any two points in function $f(x)$, and it can be seen that the gradient of function $f(x)$ at any two points will always be less than or equal to the constant M.

Parameter pruning in GANs introduces Lipschitz constraints to limit the elements in the parameter matrix, making the training process more stable. However, this method causes the proportional structure of the parameter matrix to become imbalanced. Spectral normalisation (SN) solves this problem by restricting the spectral norm of the parameter matrix in each layer of the network to satisfy the Lipschitz constraint.

(3) Gradient normalisation

Gradient Normalisation (GN) is a normalisation method that simultaneously satisfies model-based, non-sampling, and hard constraint conditions. Currently, mainstream normalisation methods find it challenging to meet all three conditions simultaneously. Unlike methods such as parameter pruning and SN, which ensure Lipschitz constraints by limiting matrix parameters, GN's computation is independent of the internal layers of the network. It formalises the discriminative model as a Lipschitz function approximator, reducing model complexity while making the gradient space smoother.

(4) Improving the structure of generative adversarial network models

When optimising the translation of historical museum visual symbols, the improved GAN model structure constructed in this paper is shown in Figure 1. A 100-dimensional noise vector is input into the generative model, and after multiple layers of transposed convolutions, generated historical museum visual symbol image samples are obtained. In this process, the normalisation method replaces the original Batch Normalisation (BN) with Standard Normalisation (SN), and Self-Attention (SA) is added to the last two layers of transposed convolutions. The generated historical museum visual symbol image samples and the original images are then input into the discriminative model. After multiple convolutional operations in the discriminative model, the probability value of the image being a real training image is obtained. Similarly, in the discriminative model, the normalisation method uses SN, and SA is added to the last two convolutional layers. Additionally, GN is used to constrain the model during the training process of the discriminative model. Finally, the parameters of the generative model and discriminative model are updated separately through backpropagation.

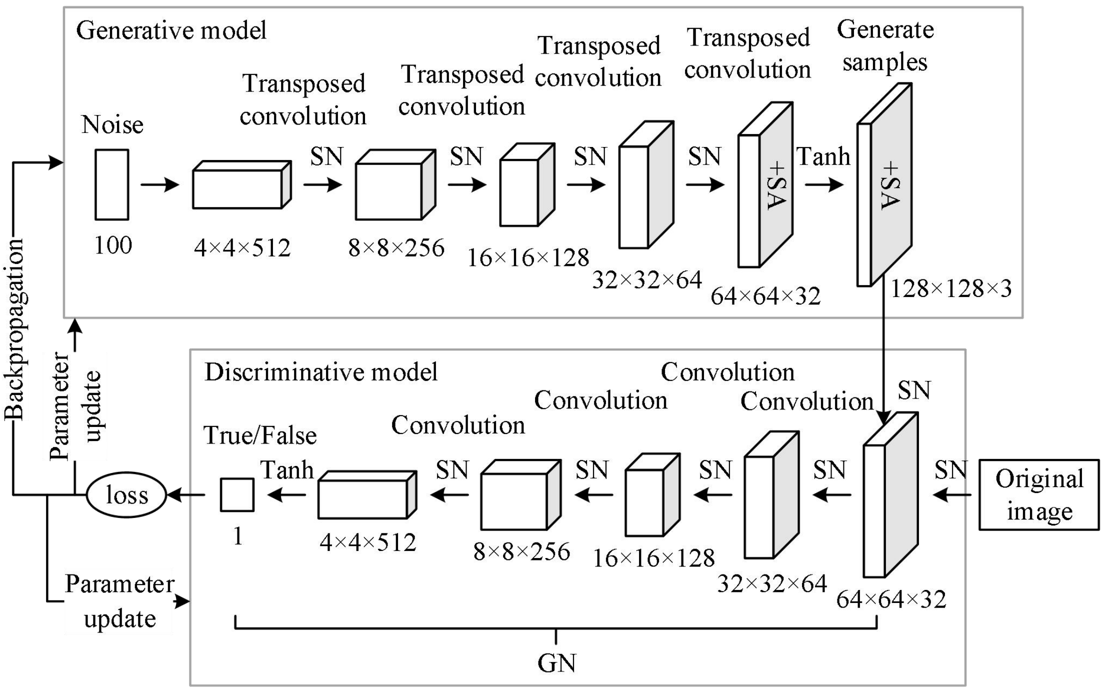


Figure 1. Structure of improved generative adversarial network.

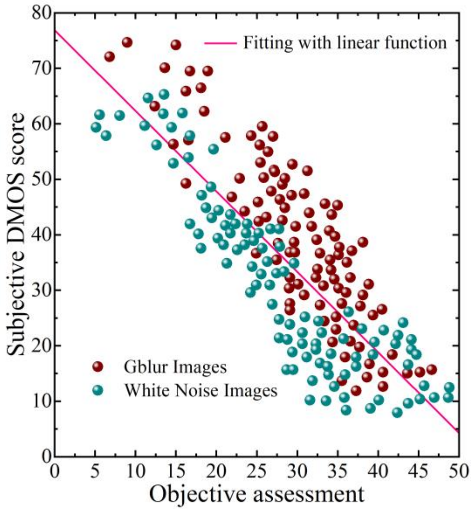
4. Validation analysis of visual semantics in historical museums

The dynamic reconstruction of spatial narratives has never received such high attention in the museum sector. As visitors shift their focus from individual, isolated objects to interconnected groups of exhibits, their attitude towards visiting museums has shifted from curiosity to the pursuit of meaning, and from appreciation of the physical appearance of exhibits to exploration of their cultural significance. The spatial narratives of history museums, as an intimate and effective means of communication, have naturally become an important tool for enhancing the cultural education effect of history museums.

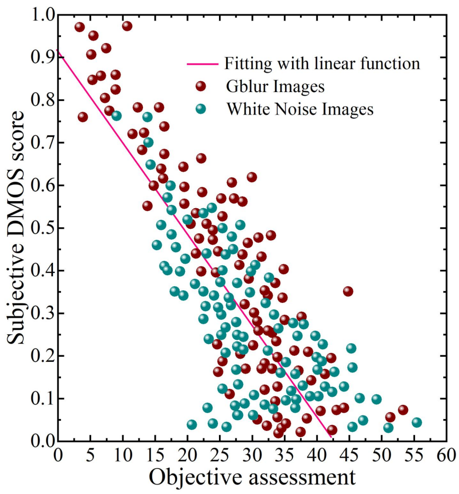
4.1. Visual symbol extraction and keyword clustering

4.1.1. Effectiveness of visual symbol extraction

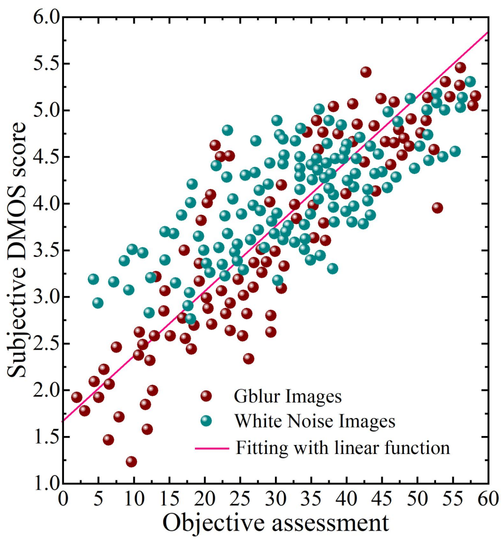
To achieve dynamic reconstruction of spatial narratives in historical museums, this paper uses filters to symbolically represent artefacts in historical museums and introduces CNN to extract visual symbol features of historical museum artefacts. To validate the effectiveness of this paper's method, three different types of image databases were selected for testing. The LIVE database provides 180 blurred images and 180 white noise images, each containing 45 original images and 135 images with varying degrees of distortion. The CSIQ database provides 160 blurred images and 160 white noise images, obtained from 40 original images subjected to four different levels of distortion. The TID2016 database provides 120 blurred images and 120 white noise images, obtained from 20 original images subjected to six different levels of distortion. The results of the objective evaluation of the final images and the subjective evaluations provided by each image database are shown in Figure 2, where Figures 2(a) to (c) are the scatter plots for LIVE, CSIQ, and TID2016, respectively. As can be seen from the figure, the evaluation results of the visual symbol feature extraction algorithm for historical museum artefacts proposed in this paper are in good agreement with the subjective evaluations.



(a) LIVE



(b) CSIQ



(c) TID2016

Figure 2. The extraction effect of visual symbols.

To further assess the consistency between the objective evaluation scores and subjective ratings of the algorithm presented in this paper, we first performed a nonlinear regression using a logistic function with five parameters on the objective evaluation scores and the subjective ratings provided by the database. The HFSS-PSNR and HFSVD algorithms were selected for comparison, with the linear correlation coefficient (CC) and Spearman correlation coefficient (SROCC) used as evaluation metrics. CC reflects the accuracy of objective predicted scores relative to subjective scores, while SROCC reflects the consistency of monotonicity between objective predicted scores and subjective scores. Both values range from 0 to 1, with higher values indicating better algorithm performance. The performance results of the three algorithms on different types (fuzzy and white noise) are shown in Table 1.

As can be seen from the data in the table, the HFSS algorithm performs better than the algorithm proposed in this paper when evaluating Gaussian white noise images. The HFSVD algorithm also demonstrates greater subjective consistency than the algorithm proposed in this paper when evaluating Gaussian blurred images. However, the HFSS algorithm is not suitable for evaluating blurred images, as it has limitations when evaluating images with severe blurring, resulting in poorer performance. The HFSVD algorithm also cannot effectively evaluate Gaussian noise images. Therefore, when evaluating blurred distorted images alone, the HFSVD algorithm performs best, while the HFSS algorithm is most effective in evaluating noise images. Considering that the algorithm proposed in this paper is primarily applicable to the extraction of visual symbols from cultural relics in historical museums, where images may be blurred and contain Gaussian noise, although the algorithm performs slightly worse when evaluating Gaussian noise images and Gaussian blurred images, it can evaluate both types of distorted images simultaneously, making it the most versatile. Applying it to the extraction of visual symbols from cultural relics in historical museums is more feasible and can assist in the translation of historical cultural relic visual symbols.

Table 1. Performance comparison results of the algorithm.

Algorithm	Type	LIVE	CSIQ	TID2016
Ours (Gblur)	CC	0.7563	0.8547	0.8013
	SROCC	0.6812	0.7984	0.8094
Ours (Write Noise)	CC	0.9127	0.7189	0.5865
	SROCC	0.9213	0.7374	0.6081
HFSS (Write Noise)	CC	0.9459	0.7372	0.6737
	SROCC	0.9463	0.7287	0.6685
HFSVD (Gblur)	CC	0.7903	0.8001	0.6859
	SROCC	0.8419	0.8492	0.6922

4.1.2. Keyword clustering of spatial narratives

Keywords are a highly condensed representation of the themes and core elements of the dynamic reconstruction of spatial narratives in historical museums. Through in-depth analysis of keyword co-occurrence and clustering, as well as timeline diagrams and temporal maps, one can gain insights into the development trends and optimisation directions of a historical museum's spatial narrative. From a knowledge theory perspective, high-frequency keywords can highlight the common focus of historical museums during a specific period. Centrality, as an indicator of node influence, can reveal its core position in the spatial narrative of historical museums. The co-occurrence frequency of keywords is directly proportional to their point centrality, indicating their importance in the field. Based on this, this paper takes the artefact data and related tag data displayed in the BJ Historical Museum as the research object and collects and integrates various types of data. The TF-IDF algorithm is used to extract the spatial semantics of artefacts in historical museums, and the FCM clustering algorithm is then applied to cluster them, resulting in the keyword clustering map for the spatial narrative design of historical museums, as shown in Figure 3. Table 2 presents the clustering results of the keyword co-occurrence map.

Based on the clustering results, the modularity Q-value of the clustering map is 0.839 > 0.35, indicating that the clustering is effective. The average contour value is 0.943 > 0.75, indicating that the clustering modules are convincing and the clustering results are reasonable. From the clustering map, nine clusters have been formed: #0 Historical Museum, #1 Narrative Techniques, #2 Spatial Narrative, #3 Cultural Space, #4 Narrative Mechanisms, #5 Memory Space, #6 Narratology, #7 Cultural Heritage, and #8 Cultural Relics Revitalisation. The optimisation of spatial narrative design in historical museums primarily revolves around these clusters, revealing trends in the optimisation of exhibition design and dynamic reconstruction of spatial narratives in historical museums. The focus of these trends lies in enhancing cultural communication through spatial narrative design, thereby improving users' emotional experiences and sense of belonging. The dynamic reconstruction of spatial narratives in historical museums is increasingly assuming the role of preserving and transmitting cultural memories of artefacts, thereby facilitating the reinterpretation of traditional artefacts and culture within contemporary spatial contexts.

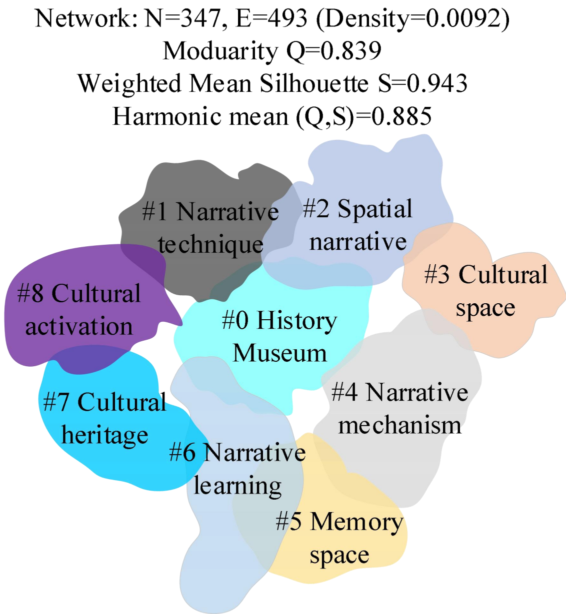


Figure 3. Keyword clustering graph for spatial narrative design.

Table 2. The clustering results of the keyword co-occurrence map.

Clustering	Number of key words	Average contour value	Main keywords	Clustering label
#0	48	0.953	Museums; Exhibition narrative; Spatial narrative; Exhibition; Narrative design	History museum
#1	41	0.947	Narrative; Public space; Spatial narrative; Posters; Syrian	Narrative technique
#2	36	0.856	Spatial narrative; Cultural revitalization; Display design; Museums; narrative	Spatial narrative
#3	30	0.983	Cultural space; Cultural relics narrative; Space; place	Cultural space
#4	27	0.911	Narrative mechanism; Identification; Space language; Logic; context	Narrative mechanism
#5	21	0.932	Memory space; Value; Evaluation indicators; Create; time	Memory space
#6	18	0.938	Narrative learning; Museums; Exhibition space; Cultural memory; redemption	Narrative learning
#7	15	0.974	Cultural heritage; Collective memory; Chinese history; Archives exhibition; Public history	Cultural heritage
#8	10	0.995	Cultural relics; Chinese cultural relics; Narrative technique; Space design; Narrative thinking	Cultural activation

4.2. Objective analysis of visual symbol translation performance

4.2.1. Comparison of translation performance results

To validate the effectiveness and reliability of the proposed method and network model, simulation experiments were conducted under the same experimental environment and equipment configuration. The experimental hardware environment used a 16-core server with an Intel(R) Xeon(R) Silver CPU @ 2.80 GHz*2, 32G memory, and an NVIDIA RTX 3090Ti graphics card. The deep learning framework used was PyTorch, and programming was performed using Python.

The performance of the translation results for visual symbols of historical museum artefacts was evaluated using peak signal-to-noise ratio (PSNR) and structural similarity (SSIM). Under the same experimental conditions, the effects of the classic Bicubic, SRCNN, SRGAN algorithms and the proposed method on model translation were further compared by calculating the PSNR and SSIM of the translation results of the above methods to objectively compare their effects. PSNR is a key technical indicator for characterising image quality; the higher the PSNR value, the better the quality of the target translated image. SSIM is a perceptual metric used to quantify the degree of image quality degradation; the higher the SSIM value, the higher the image translation quality. Figure 4 shows the comparison results of visual symbol translations under different scaling factors.

As shown in the figure, when the scaling factor is 3, the method proposed in this paper achieves PSNR values that are 3.84 dB, 1.21 dB, and 2.17 dB higher than those of the Bicubic, SRCNN, and SRGAN methods, respectively, in the translated images of cultural relics. In terms of structural similarity, the proposed method achieves values of 0.0474, 0.0211, and 0.0087 higher than Bicubic, SRCNN, and SRGAN, respectively. When the scaling factor is 6, the peak signal-to-noise ratio of the proposed method is 27.78 dB, which is 11.97%, 6.56%, and 7.14% higher than Bicubic, SRCNN, and SRGAN, respectively. In terms of structural similarity, the proposed method outperforms Bicubic, SRCNN, and SRGAN by 4.63%, 2.01%, and 2.15%, respectively. Based on the 3x and 6x super-resolution translation results of low-resolution historical museum artefact images, the proposed method achieves better translation results than the other three methods in terms of PSNR and SSIM. However, when the scaling factor is 6, the super-resolution evaluation metrics are relatively low, indicating greater reconstruction difficulty. Nevertheless, compared to other methods, the proposed method still achieves the highest PSNR and SSIM values at a scaling factor of 6x.

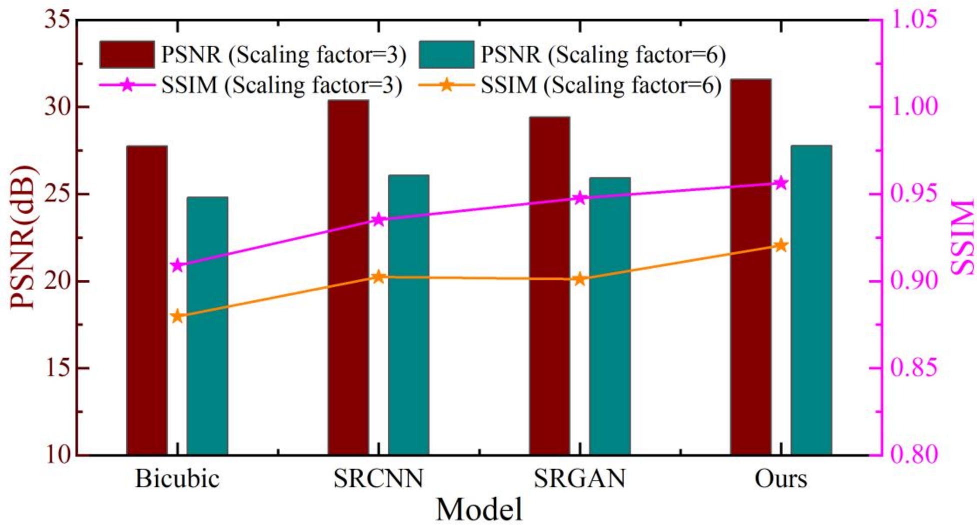


Figure 4. Results of visual symbol translation under different scaling factors.

The results indicate that under the same experimental conditions, the proposed method achieves the optimal PSNR and SSIM values when translating cultural relic images using 3x and 6x super-resolution. Compared to the other three methods, this method yields superior cultural relic image translation results, which is crucial for optimising the spatial narrative effect of cultural relics in historical museums.

4.2.2. Ablation experiments of translation models

To validate the role of self-attention mechanisms, spectral normalisation, and gradient normalisation in GANs, we conducted ablation experiments. Specifically, we added SA, SN, and GN to GANs separately and conducted various combination experiments. We used the decision tree (DT) algorithm for classification and evaluated model performance using four metrics: accuracy, precision, recall, F1 score, and AUC. The experimental results are shown in Table 3.

An overall analysis of the data in the table shows that, compared to other models, the original GAN has the lowest recall rate, indicating that it has certain limitations in capturing minority class samples. After adding the SN module to the original GAN model, its accuracy improved to a certain extent. After adding the self-attention mechanism module, the recall rate and F1 score improved significantly. After adding the GN module, all indicators improved steadily. In the ablation experiment, the model's performance reached its optimal level after adding SA, SN, and GN to the original GAN, with particularly significant improvements in recall rate and F1 score. For example, the model's recall rate increased from 0.7588 in the original GAN to 0.8324, indicating enhanced recognition capability for minority classes. Therefore, the SN module, GN module, and self-attention mechanism can all independently improve GAN performance, with the GN module having the most significant effect. The synergistic effect of module combinations is evident, with the three-module combination achieving optimal performance on the dataset. The self-attention mechanism makes a notable contribution to improving recall rate, making it suitable for tasks requiring focus on minority classes, while the GN module helps improve model stability. The complexity of the dataset influences module performance, with greater optimisation potential for modules on the underperforming original model.

Table 3. Ablation experiment of the translation model.

Model	Accuracy	Precision	Recall	F1 value	AUC
GAN	0.8142	0.8509	0.7588	0.8013	0.8642
GAN+SN	0.8323	0.8645	0.7761	0.8185	0.8838
GAN+SA	0.8261	0.8751	0.7864	0.8278	0.8996
GAN+GN	0.8495	0.8892	0.7981	0.8406	0.8915
Ours	**0.8672**	**0.9045**	**0.8324**	**0.8692**	**0.9207**

4.3. Spatial Narrative Expression in History Museums

4.3.1. Strategic Analysis of Spatial Narratives

In traditional exhibitions at historical museums, the linear narrative model is the most common approach, typically arranging exhibits in chronological order or according to the sequence of historical events. While this method is logically clear, it can appear monotonous and rigid in the complex, multi-layered spaces of historical museums. Based on this, this paper takes the BJ History Museum as a case study and employs four narrative optimisation methods—spatial narrative reconstruction, architectural element transformation, lighting system re-creation, and immersive scene creation—using visual symbols of historical artefacts obtained through an improved GAN. Before and after designing the corresponding optimisation strategies, 30 participants were selected for an experiential analysis, and their experiential satisfaction was scored on a scale of 1 to 5. The scores of the 30 participants' pre- and post-experiential satisfaction were statistically analysed, yielding the optimisation comparison results of the spatial narrative strategies, as shown in Figure 5.

As shown in the figure, prior to implementing the dynamic reconstruction and optimisation strategy for the spatial narrative of the historical museum, the average experience score of the participants was only 2.48. However, after implementing the four spatial narrative optimisation strategies, the average experience score of the participants increased by 61.69%. In the spatial narrative reconstruction, historical artifacts and museum scenes can be mutually responsive, using a combination of virtual and real display methods to both define spatial divisions and establish an intertextual relationship between the historical functions of the museum building space and the exhibition content. Participants can directly perceive the changes in artifacts over history during their visit, truly achieving the narrative effect of ‘space telling history.’ The architectural element conversion method provides natural visual guidance for participants. Combined with a dual lighting control mode of ‘obscuration-reconstruction,’ adjustable-angle spotlights and reflective lighting are used to achieve an exhibition illuminance standard of 220–360 lux in the museum. Adjustable-angle spotlights can precisely adjust the lighting angle and intensity according to the characteristics of the exhibits and display requirements, highlighting the details and texture of the exhibits. Reflective lighting uses devices such as reflectors to bounce light onto exhibits, creating a soft, even lighting effect and avoiding glare and shadows that may result from direct illumination.

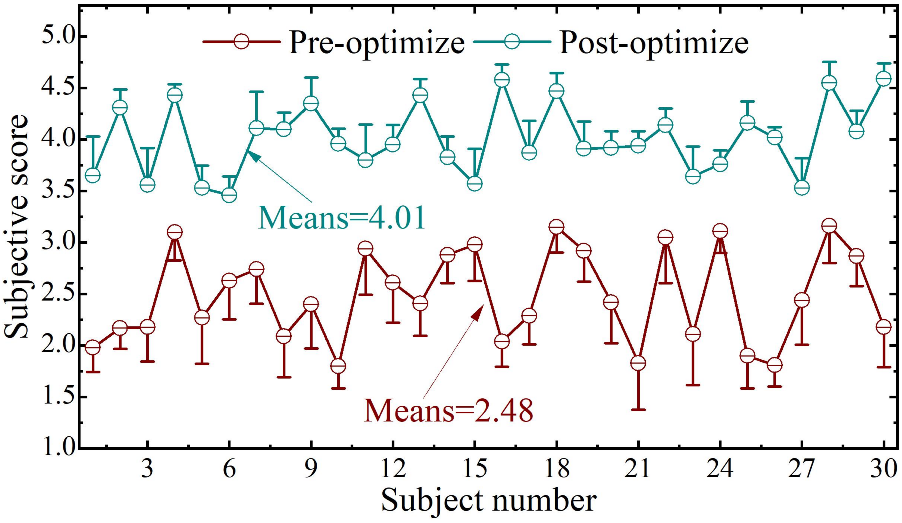


Figure 5. Optimization comparison of spatial narrative strategies.

Additionally, in the process of creating an immersive environment, the exhibition methods for cultural relics in historical museums have been innovated, breaking away from traditional layout display models to establish a three-tiered immersive system comprising ‘architectural scenes, historical scenes, and experiential scenes.’ By employing a ‘scene construction + interactive experience’ approach, the existing architectural layout of historical museum spaces is utilised to form natural display areas, integrating the displays into the museum environment. This allows participants to acquire knowledge as they move through the changing scenes. Additionally, LED screens are installed to provide detailed explanations of the origins of each artefact, deepening participants' understanding of the cultural significance of the exhibits and enhancing the historical museum's brand reputation.

4.3.2. Updating the narrative mechanism of museums

Space is “compressed” and “folded” under the influence of media technology and information flow, thereby subverting people's traditional linear perception of time and space. Building on the optimisation strategies for spatial narrative design in historical museums, this study further explores the cross-media narrative characteristics of spatial narrative design supported by technology. Spatial narrative design serves as both a tool to reveal the multi-layered interactions between media and space and a design discourse system that integrates perceptual, interactive, and meaningful elements. It connects virtual and real spaces by imbuing “designed objects” with event-based narrative contexts. Figure 6 illustrates the cross-media narrative characteristics of spatial narratives in historical museums. These primarily include media characteristics such as mediatisation, spatialisation, heterogeneity, and criticality. Spatial narrative connects the social material environment with individual perception, transforming it into embodied cognitive experiences. Spatial narrative transforms social values and individual emotions into specific spatial contexts, providing spatiotemporal interactive experiences. Spatial narrative accommodates social cultural symbols and behavioural differences, generating symbolic everyday experiences. Spatial narrative mediates the dialogue between social rights structures and ideologies, creating value-reflective experiences. The spatial narrative design of historical museums not only spatialises social relationships and mediates spatial meanings but also possesses the social utility of accommodating heterogeneity and triggering critical reflection. The spatial narrative design of historical museums not only constructs social spaces and organises mediating behaviours but also possesses information dissemination functions. As a cross-media narrative method, its core lies in guiding users to participate in the experience of the narrative space through storytelling, thereby achieving recognition of spatial meanings.

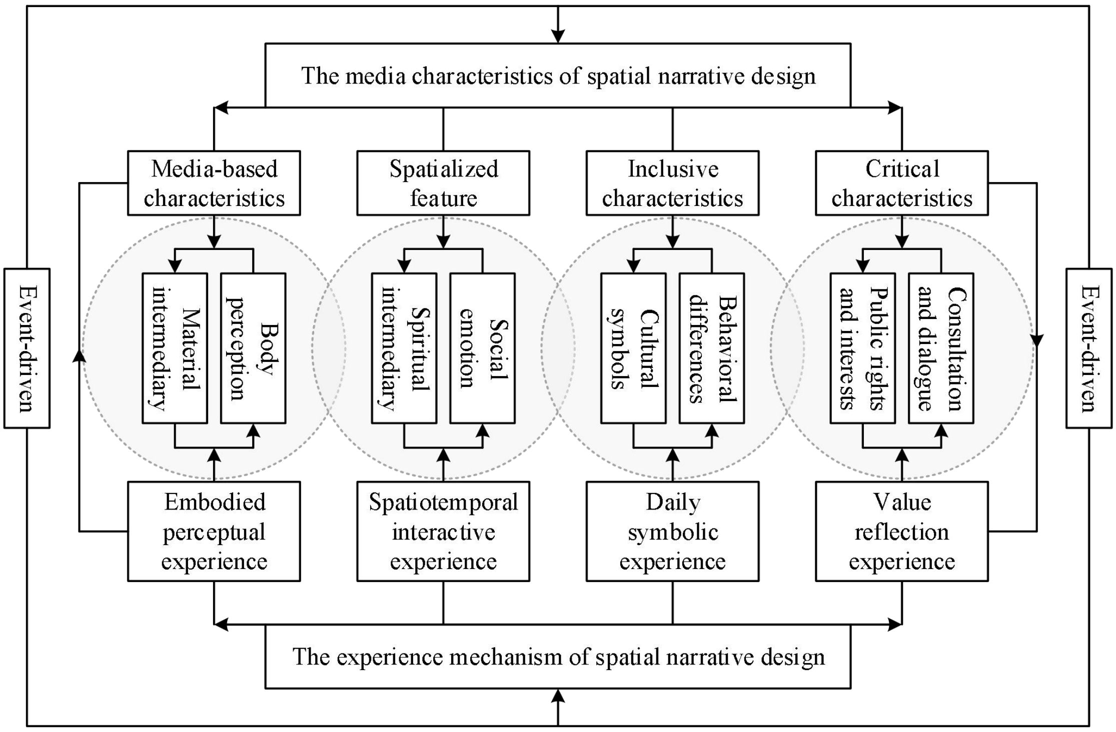


Figure 6. Spatial narrative design features cross-media narrative characteristics.

Building on this foundation, this paper further analyses the evolving trends in the narrative spaces of historical museums, specifically memory space, knowledge space, cultural space, and discursive space. Based on these four narrative spaces, corresponding survey questionnaires were designed to validate the extent to which audiences recognise the narrative effectiveness of the spatial design at the BJ Historical Museum. The survey questionnaire employed a Likert five-point scale for data quantification, with scores ranging from 1 to 5 representing "strongly disagree," "disagree," "neutral," "agree," and "strongly agree," respectively. The survey questionnaires were primarily distributed through the Questionnaire Star platform, with a total of 1,000 questionnaires distributed. The effective response rate of the survey questionnaires was 94.8%. After organising the data from the survey questionnaires, the audience's recognition of the narrative reconstruction effect of the BJ Historical Museum's spatial narrative is shown in Table 4.

Based on the data from the survey questionnaire, it can be seen that the audience's overall recognition of the dynamic reconstruction effect of the spatial narrative in the BJ History Museum is relatively high, with the average proportion of respondents who expressed recognition and strong recognition reaching 80.05%. This suggests that the narrative space is effectively realised within the BJ History Museum, enabling audiences to achieve effective integration of the cultural semantics of artefacts. This helps visitors to better engage in perceptual experiences, cognitive experiences, daily experiences, and discursive experiences, further stimulating audiences' memory of historical culture, enhancing their emotional and cultural identification with historical culture, and laying the foundation for the cultural educational significance of the history museum.

Table 4. The recognition of the effect of spatial narrative reconstruction (%).

Space		1	2	3	4	5
Memory	Perceptual experience	2.79	5.61	9.85	58.71	23.04
	Emotional identity	4.58	6.38	10.41	63.12	15.51
Knowledge	Cognitive experience	3.37	6.82	12.37	56.58	20.86
	Interactive participation	2.61	5.83	13.19	65.33	13.04
Cultural	Daily experience	3.16	6.09	10.06	57.46	23.23
	Cultural identity	3.55	3.25	10.67	55.69	26.84
Discourse	Discourse experience	3.44	5.82	11.31	53.85	25.58
	Consultative dialogue	3.32	4.89	10.24	51.27	30.28

5. Conclusion

The article extracts visual symbols from historical museums and conducts a cluster analysis of their spatial semantic characteristics. It then combines an improved GAN model to translate the visual symbols of historical museums and uses simulation experiments to analyse the translation effect of the visual symbols of historical museum spatial narratives, exploring the spatial narrative performance of historical museums. The study found that the spatial narrative features of historical museums encompass nine distinct types of labels, and the overall performance of the translation model meets the expected requirements. Additionally, after optimising the spatial narrative strategy, the participants' experience satisfaction score reached 4.01, with over 80% of the audience expressing approval for the updated spatial narrative mechanism of historical museums.

Based on this, it is necessary to further emphasise innovation in the dynamic reconstruction of spatial narratives in historical museums. New technologies can be introduced to help build more comprehensive and immersive scene experiences. This will better stimulate the audience's interest in historical museums, enhance their appeal to visitors, and provide new opportunities for the innovative revitalisation of historical culture in historical museums.

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