ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 2 - 2026

Innovative Application Strategies of Regional Traditional Cultural Symbols in Boutique Theme Hotel Space Creation

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SUMMARY: *In recent years, more and more cities pay attention to the display of urban culture in the construction of hotels, and take the hotel space as a propaganda and display carrier of their own regional cultural symbols, extending the use value and cultural value of the hotel space. In this paper, based on the spatial design and creation method translated by AIGC, CBAM is added on the basis of the traditional ResNet-50 model, which significantly improves the feature extraction capability by integrating the strategies of channel attention and spatial attention. Multi-scale features are extracted and the CBAM module is utilized to enhance the key feature responses for dynamic decoupling, which are subsequently co-mapped with the textual semantics to the embedding space of the CLIP text encoder to complete cross-modal alignment. The diffusion model is used to simulate the cultural symbols based on emotional perception, and the LoRA model is used to fine-tune a very small number of parameters to complete the directional migration of the characteristics of the traditional regional cultural symbols, and to design a boutique themed hotel space containing regional cultural symbols. Analyzing the hotel space and cultural development fitness, all the hotels have high spatial accessibility, with a mean value of 3.597, but still have spatial development potential. The overall spatial satisfaction of the H6 hotels designed through the methodology of this paper is high, with all space types above 80%, but there is a need for improvement in the design of semi-open spaces.*

KEYWORDS: *AIGC; CBAM; LoRA; CLIP text encoder; regional cultural symbols; space creation*

1 Introduction

With the development of tourism and the economy, tourists to accommodation and service requirements, only to provide basic accommodation hotels have been unable to stand in today's consumer era, the hotel created for the spiritual dimension of the experience will be more attractive, and boutique, themed is a change in the hotel industry [1-3]. Boutique theme hotel theme is more emphasis on the spiritual level, including culture, personality, memory and so on. However, the current boutique theme hotel space on the homogenization of serious, obsolete design concepts, the spiritual level of support is weak, resulting in insufficient visitor experience and loyalty decline, hotel competitiveness is insufficient [4-6].

In recent years, the study of regional traditional culture has been heating up, and regional cultures all over the country are called by their own characteristic culture. Interior design projects themed on regional traditional culture are also common. Such as the Qing culture as

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https://doi.org/10.65102/is2026666

Published: 30 April, 2026

the regional theme characteristics of the Shenyang Qing culture theme hotel, the capital culture as the theme of the Beijing Wangfujing Hotel, the marine culture as the theme of the underwater world of Hainan Hundao hotel and so on. The regional traditional cultural symbols, as the cultural markers precipitated in the region over a long period of time, enrich the cultural connotation of the hotel with highly distinctive and emotional historical and aesthetic values, create a space for tourists to immerse themselves in the local culture, and strengthen the sense of cultural identity and cultural understanding of the tourists [7-10]. Designers use regional cultural symbols to strengthen the differentiation of the theme hotel space and enhance the image of the hotel in order to promote the core competitiveness of the hotel and enrich the tourists' travel experience [11].

This paper summarizes and concludes the strategy of cultural symbols translation in architectural space, uses AIGC technology to achieve regional traditional cultural symbols style migration, and introduces CBAM in ResNet-50 structure to strengthen the extraction ability of cultural symbols style features. Multi-scale features are extracted using the improved ResNet-50 model and dynamic decoupling of features is realized by CBAM module. The spatial alignment method is applied to cross-modal alignment of visual features and textual semantics to effectively generate semantically coherent and culturally adapted content, which provides strong support for the innovative design of regional traditional culture. Train the above model, use the LoRA model with inserted low-rank adaptation module, and micro-tune a very small number of parameters for the diffusion model to complete the feature-guided low-rank semantic migration. The design scheme of space creation of theme hotel is proposed, and the effect of cultural symbols of regional traditional culture in hotel space creation is evaluated by means of random survey.

2 Translation of regional cultural symbols and creation of spatial context

2.1 Strategies for Translating Cultural Symbols in Architectural Space

In modern architectural space design, the translation of symbols is not only the inheritance of traditional art forms, but also the contemporary interpretation and innovation of its cultural symbols. Traditional cultural symbols are often reconstructed in the design language, and through the combination of modern technological means and design concepts, design elements that meet modern aesthetic and practical functional needs are formed. This process of translation is not only the respect and reproduction of traditional culture, but also the continuation and sublimation of its symbolic meaning.

(1) Language Translation

The translation of regional traditional cultural symbols relies on the re-cognition of historical symbols. In architectural space design, designers often simplify and abstract the cultural symbols to retain their cultural connotation while adapting them to the needs of modern architectural space.

(2) Color and texture

The color and texture of cultural symbols also play an important role in the process of spatial translation. In modern architectural design, designers can create a layered and dynamic spatial effect through the combination of light and shadow changes and material texture.

(3) Emotional expression

Most importantly, the translation of regional traditional cultural symbols is not only limited to the visual effect, it should also pay attention to the emotional transmission of the symbols in the spatial atmosphere. Natural texture, exquisite modeling and deep cultural deposits make it an important link between history and modernity, art and life in architectural decoration. Through the skillful use of these symbols, designers can make the space not only have aesthetic value, but also trigger the emotional resonance and cultural identity of the viewers.

2.2 Spatial Design Creation Method Based on AIGC Translation

(1) Symbol decoding - establishing the connection point between culture and technology

Using CBAM, ResNet and other methods, we systematically disassemble regional cultural symbols, extract quantifiable visual elements (color values, morphological parameters, pattern vectors), transform them into the recognizable “language” of the AIGC model, extract morphological features, and construct a structured symbol database.

(2) Algorithm training - customized model development and optimization

Based on the symbol database, we cooperate with technicians and use lightweight training methods such as LoRA to fine-tune the parameters on the basis of general AIGC models (e.g., Stable Diffusion), so as to train exclusive models with regional cultural styles, and ensure the cultural authenticity of the generated results.

(3) Generation Optimization - Creative Iteration with Human-Machine Collaboration

Through the design of Prompt instructions, the model is guided to generate a preliminary design plan, which needs to take into account the cultural accuracy and creative openness. For the generation results, screening and optimization are carried out in three dimensions: cultural connotation, visual aesthetics and technical feasibility, forming an iterative process of “AI generation - manual screening - secondary generation”.

3 Intelligent Translation of Regional Cultural Symbols and Space Creation Technology

3.1 Stylistic migration of regional traditional cultural symbols based on AIGC

3.1.1 Analysis of cultural symbols

The deep network of traditional ResNet-50 may lead to the attenuation of low-level features, which makes it difficult to retain the details in cultural symbols, while the negative gradient truncation of cultural symbols by traditional ReLU exacerbates the loss of details. To further enhance the model's ability to recognize key features of regional traditional cultural symbols, CBAM is introduced into the ResNet-50 structure, which significantly improves the feature extraction ability by integrating the strategies of channel attention and spatial attention. CBAM performs a weighting operation on the input features, enhances the important features, suppresses the unimportant features, and finally outputs the enhanced features. The process of generating attention is shown in the following equations (1) and (2), and its structure and operation process are shown in Fig. 1:

$$F' = M_c(F) \otimes F \tag{1}$$

$$F'' = M_s(F') \otimes F' \tag{2}$$

where F is the input feature, $M_c(F)$ is the channel attention map, $\otimes$ denotes element-by-element multiplications, F' is the result after channel operations, $M_s(F')$ is the spatial attention map, and F'' is the output after feature enhancement.

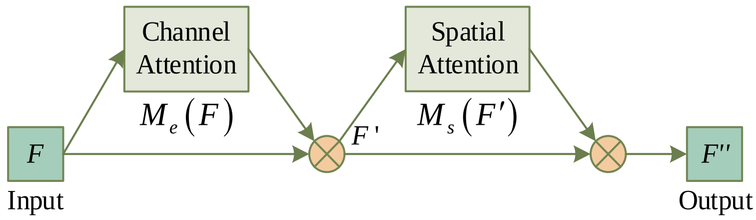

Figure 1: The structural composition of CBAM

The original ResNet-50 uses the ReLU activation function, which is widely used because it is computationally simple, fast to train, and has shown good results in practice.The ReLU function is shown in equation (3):

$$f(x) = \max(0, x) \tag{3}$$

However, ReLU has some limitations when dealing with negative inputs, i.e., for negative values, there is the problem that some neurons may never activate. The shortcomings of the ReLU function are effectively addressed by the Exponential Linear Unit (ELU), which is shown in equation (4):

$$f(x) = \begin{Bmatrix} x, x > 0 \\ \alpha\left(e^x - 1\right), x \leq 0 \end{Bmatrix} \tag{4}$$

where α is a parameter greater than 0, α needs to be tuned for best results.

The ELU function gradually decreases the output when the input is less than 0, rather than truncating to 0 directly, thus maintaining a certain gradient and avoiding the problem that neurons may never activate. Although the computational cost of the ELU function is higher than that of ReLU, the trained model is more suitable for processing image data with complex features.

Based on the above analysis, a new model that incorporates the CBAM attention mechanism and improves the ResNet-50 structure is proposed. Specifically, the new model adds a CBAM module after each convolutional block of ResNet-50, which enables the network to adaptively pay attention to the important regions and channels in the images of regional traditional cultural symbols, thus improving the classification performance. Meanwhile, in order to enhance the model's ability to express complex nonlinear features, the traditional activation function ReLU is replaced with ELU. this improvement helps to alleviate the problem of gradient vanishing in the deep network, and improves the model's convergence speed and generalization ability. In addition, the new model retains the residual connection structure of ResNet-50, which effectively mitigates the degradation problem caused by network deepening.

3.1.2 Multi-scale feature extraction and decoupling

In the identification of regional traditional culture and parsing of cultural symbols, the improved ResNet-50 model proposed in this paper realizes multi-scale feature extraction through residual blocks to construct a hierarchical feature representation. The model is able to gradually extract detailed features and semantic information of cultural symbols from low to high levels, while enhancing the response of key features through CBAM module to realize dynamic decoupling of features.

The model extracts cultural features through three layers of residual blocks. The low-level features capture the edges, base pattern contours and color distributions of the culture with a feature map dimension of $56 \times 56 \times 256$. Mid-level features resolve the spatial layout of cultural components with a feature map dimension of $28 \times 28 \times 512$. High-level features encode the overall style and geographical semantics of the culture, with a feature map dimension of $14 \times 14 \times 1024$.

The CBAM module embedded in each residual block dynamically enhances the key feature responses through a channel-space bi-dimensional attention mechanism. The channel attention generates channel weights through global average pooling with fully connected layers, as shown in equation (5):

$$Channel\ Attention = \sigma\left(W_2 \delta\left(W_1 F_{gap}\right)\right) \tag{5}$$

where F_{gap} is the global average pooled features, W_1 and W_2 are the fully connected layer weights, δ is the ReLU activation function, and σ is the Sigmoid function.

In order to separate the independent attributes of cultural symbols from the features of each layer, feature decoupling is realized by using feature post-processing algorithm. Color decoupling constructs color descriptors by extracting the RGB value of the main color through K-Means clustering of the low-level feature map. Tattoo decoupling uses the high activation region of the middle-level features to generate the edge response map, extracts the topology of the tattoo through morphological operations, performs principal component analysis on the high-level features, and visualizes the distribution of regional style clustering through t-SNE after dimensionality reduction.

3.1.3 Cross-modal semantic mapping

In cross-modal generation tasks, achieving alignment between visual features and textual semantics is a critical step in generating high-quality content. To this end, this study proposes a latent space alignment method, $f_{joint} \in R^{1792}$ and maps it to the embedding space of the CLIP text encoder through a linear projection layer. Specifically, the mapping process is realized through the fully connected layer Proj, as shown in equation (6):

$$c = \mathrm{Proj}\left(f_{joint}\right) \tag{6}$$

where $\mathrm{Proj}: R^{1792} \to R^{768}$ is a fully-connected layer to realize cross-modal alignment of visual features with textual semantics.

In the generative condition construction stage, structured textual cues are generated based on the mapped embedding vector c, combined with artificial rules. The text cues are in the form of:

"Ethnic style: {style}, primary colors: {colors}, core motifs: {patterns}, modern design requirements: {requirement}"

The specifics of each of these placeholders are as follows:

{style}: obtained from the t-SNE clustering labels of high-level features, describing the overall style of the regional traditional culture.

{colors}: converted from the RGB values of the clustering centers of the low-level features, indicating the main color of the cultural symbols.

{patterns}: parsed into semantic descriptions based on the edge response maps of the mid-level features, reflecting the core patterns of the culture.

In this way, the generated textual cues not only contain semantic information about the visual features, but also incorporate modern design requirements, providing rich semantic guidance for subsequent generation tasks. This method of potential spatial alignment and generative condition construction can effectively enhance the semantic consistency and cultural adaptability of the generated content, providing strong support for the innovative design of regional traditional culture.

3.2 Stable Diffusion

3.2.1 Diffusion probability model

Mathematically, assuming that the original data distribution is $x_0 \sim q(x_0)$, the forward process is defined by $x_t \sim q\left(x_t \middle| x_{t-1}\right)$, which adds noise to the data at each moment t until the Tth step yields an approximately pure noise x_T. The reverse process then learns a generative model $p_\theta\left(x_{t-1} \middle| x_t\right)$ that allows it to progressively reduce the data from a noisy state at any t moment. The process relies on algorithms such as backpropagation and gradient optimization to learn the parameters and generate high-quality samples.

By iterating through the forward and backward processes, the diffusion model is able to gradually learn the underlying distributional characteristics of the data, generating image samples with a high degree of fidelity and structural consistency. This modeling approach shows applicability in many fields, especially in image generation tasks, the diffusion model can be used to simulate the evolution of diffusion of visual attributes such as color, texture, and illumination in space, and through the introduction of initial randomness or external conditions, the model is able to generate controlled and diverse image content.

In the application of regional cultural symbol image generation, the diffusion model provides a method to simulate the evolution of cultural symbol generation based on emotional perception. The key lies in the setting of the diffusion coefficient and the initial conditions, and the appropriate parameter configuration has an important impact on the clarity, detail expressiveness, and relevance to the text of the generated image. The result analysis of the generated images includes quantitative assessment and qualitative analysis of the images to verify the applicability and generation effect of the model in the generation of cultural symbol images.

Diffusion probabilistic models (DPMs) achieve data generation by defining a forward noise perturbation process and an inverse denoising process. The forward process constructs a Markov chain to gradually transform the data distribution $q(x_0)$ into an isotropic Gaussian noise distribution with the following formula:

$$q\left(x_1 : T \middle| x_0\right) = \prod_{t=1}^{T} q\left(x_t \middle| x_{t-1}\right), q\left(x_t \middle| x_{t-1}\right) = \mathcal{N}\left(x_t; \sqrt{1-\beta_t} x_{t-1}, \beta_t I\right) \tag{7}$$

where $\{\beta_t\}_{t=1}^{T}$ is a noise scheduling parameter that satisfies $0 < \beta_1 < \cdots < \beta_T < 1$. The inverse process learns the parameterized distribution $p_\theta\left(x_{t-1} \middle| x_t\right)$, whose mean and covariance are predicted by the neural network, with the following formula:

$$p_\theta\left(x_{t-1}\middle|x_t\right)=\mathcal{N}\left(x_{t-1};\mu_\theta\left(x_t,t\right),\Sigma_\theta\left(x_t,t\right)\right) \tag{8}$$

The training objective is to minimize the mean square error between the prediction noise ϵ_θ and the true noise ϵ :

$$\mathcal{L}_{simple}=\mathbb{E}_{x_0\sim\mathcal{N}(0,I),\epsilon\sim\mathcal{N}(0,I)}\left[\left\|\epsilon-\epsilon_\theta\left(\sqrt{\bar{\alpha}_t}x_0+\sqrt{1-\bar{\alpha}_t}\epsilon,t\right)\right\|_2^2\right] \tag{9}$$

where $\bar{\alpha}_t=\prod_{s=1}^{t}\left(1-\beta_s\right)$ is the noise accumulation factor.

The core optimization of Stable Diffusion is to reduce the computational complexity by relocating the diffusion process to the potential space. By pre-training the encoder $\mathcal{E}_\phi$ of the variational auto-encoder (VAE) to compress the image $x\in\mathbb{R}^{512\times512\times3}$ into the low-dimensional latent variable $z=\mathcal{E}_\phi(x)\in\mathbb{R}^{64\times64\times4}$, the diffusion process is executed in the potential space and the computational complexity is reduced to $1/((8^2\cdot3/4))\approx5.3\%$ of the original space. The decoder $\mathcal{D}_\phi$ maps the denoised latent variable z' back into pixel space, a strategy that reduces training time by 78% while keeping the FID below 15.

3.2.2 Diffusion probability models

Stable Diffusion realizes text-to-image generation control through an innovative cross-modal attention architecture. The core of the system lies in the dynamic injection of textual semantic information into the image generation process, which is realized through the following mechanism.

Text Conditional Coding, the input text cue c is first converted into a semantic embedding vector by a pre-trained CLIP text encoder, which preserves the semantic features of the text at all levels, as shown in the following formula:

$$e_c\equiv CLIP(c)\in\mathbb{R}^{77\times768} \tag{10}$$

Cross-attention mechanism, in each residual block of U-Net, textual conditions are fused with image features through cross-attention layer with the following formula:

$$Attention\left(Q,K,V\right)=soft\max\left(\frac{QW_Q^T\left(KW_K\right)}{\sqrt{d_k}}\right)VW_V \tag{11}$$

where the query vector $Q\in\mathbb{R}^{N\times d_q}$ is derived from the latent feature z_t, the key-value vectors $K,V\in\mathbb{R}^{L\times d_k}$ are obtained from the textual embedding e_c by linear projection, and W_Q,W_K,W_V are the learnable parameter matrices. This mechanism establishes a high degree of correlation between the pixel level (image features) and the lexical element level (text features).

To further enhance the degree of control, a classifier-free guidance (CFG) strategy is used. The training phase randomly discards textual conditions with probability $p=0.1$, so that the model learns the conditional distribution $p_\theta\left(z_t\middle|c\right)$ and the unconditional distribution $p_\theta(z_t)$ in synchronization, and enhances the conditional influence by linear interpolation in the inference phase, Eq. as follows:

$$\epsilon_{\text{final}} = (1+w)\epsilon_{\theta}(z_t, t, c) - w\epsilon_{\theta}(z_t, t, \varnothing) \tag{12}$$

3.2.3 Loss Functions for Diffusion Models

In the inverse generation process of the diffusion model, in order to efficiently train the noise prediction network $\epsilon_{\theta}(x_t, t, c)$. A loss function based on noise regression is often used.Stable Diffusion commonly uses the following form of mean square error loss (MSE) to minimize the difference between the prediction noise and the true additive noise.

$$\mathcal{L}_{\text{simple}}(\theta) = \mathbb{E}_{x_0,\epsilon,t}\left[\left\|\epsilon - \epsilon_{\theta}(x_t, t, c)\right\|_2^2\right] \tag{13}$$

where x_t denotes the potential image representation after noise addition at time step t, $\epsilon \sim \mathcal{N}(0, I)$ is the sampled Gaussian noise, c is the textual condition, and ϵ_{θ} is the network that predicts the noise by diffusion modeling.

3.3 LoRA low-rank adaptation techniques

3.3.1 Basic Ideas and Mathematical Principles of LoRA

LoRA is based on the observation that although the weight matrix of a pre-trained model changes during the fine-tuning process, this change is still strongly represented in a low-dimensional subspace. Based on this, LoRA transforms the process of updating the original full weights into a training task on a set of low-rank matrices, which reduces the number of trainable parameters while maintaining model performance. Specifically, LoRA introduces two trainable low-rank matrices based on freezing the original weights of the pre-trained model, and injects the trainable low-rank decomposition matrices into each layer of the Transformer architecture through the low-rank decomposition approximation of the weight updating process, which reduces the number of trainable parameters on the downstream tasks, and requires only a very small amount of fine-tuning of the parameters to complete the migration learning.

The principle framework of LoRA is shown in Fig. 2. Random Gaussian initialization is used for A and zero initialization is used for B so that the result of multiplying these two short matrices in the initial state of training is zero, which ensures that the weights of the SD model are fully effective during the initial phase of training.

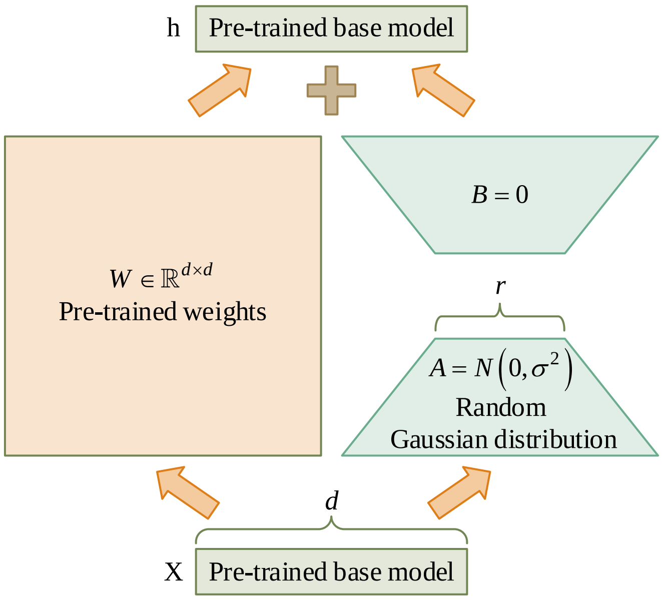

Figure 2: The principle framework of LoRA for women

Consider a weight matrix $W \in \mathbb{R}^{d \times k}$, which in conventional fine-tuning requires a full update. Whereas in LoRA, the update term is expressed as the product of two smaller matrices with the following equation:

$$W' = W + \Delta W = W + BA \tag{14}$$

where $A \in \mathbb{R}^{r \times k}$, $B \in \mathbb{R}^{d \times r}$, $r \ll \min(d,k)$ denotes the rank of the low-rank matrix, and $\Delta W = BA$ i.e., the portion of the model that is actually updated in the fine-tuning process.

By training only A and B and fixing the original pre-training parameters W, LoRA realizes a parameter-efficient fine-tuning approach.

In addition, in order to avoid interfering with the original model performance at the early stage of training, LoRA usually applies a scaling factor α to the update term, which can be used without changing the model structure or affecting the model path during the inference process, and it is a seamless and efficient strategy for integration with the following formula:

$$W' = W + \frac{\alpha}{r} BA \tag{15}$$

3.3.2 Application to depth model fine-tuning

LoRA is mainly applied to the linear transformation layers in large-scale Transformer models, especially the Query, Key and Value mapping matrices in the self-attention mechanism, to avoid updating the parameters of the whole model during the fine-tuning process and to reduce the training cost. Taking the BERT or GPT pre-training model as an example, in the fine-tuning process of downstream tasks such as text categorization and Q&A, LoRA only inserts low-rank adaptation modules into some linear layers and freezes the rest of the parameters, which is a strategy that can significantly reduce the number of parameters and the consumption of computational resources involved in the training process without affecting the performance of the model.

4 Boutique theme hotel space creation design

4.1 Auxiliary hotel theme space creation design model

4.1.1 Feature-guided low-rank semantic migration

In the fine-tuning process of diffusion modeling, traditional methods need to adjust all the parameters, which not only consumes a lot of computational resources, but also has poor adaptability in small sample scenarios. To solve this problem, LoRA technique is introduced in this study. By freezing the weights of the pre-trained model and injecting trainable low-rank matrices in the cross-attention layer, this technique realizes the directional migration of the symbolic features of regional traditional culture, which significantly improves the adaptability and training efficiency of the model under small sample conditions. The network proposed in this paper extracts the pattern, material and structural features of regional traditional cultural symbol images, and generates structured cue words, and then constructs a regional cultural semantic label library. This process not only provides rich semantic information for the model, but also provides accurate feature guidance for the subsequent low-rank adaptation. In the low-rank parameter optimization stage, the original model weight is assumed to be W_0, and the parameters are updated by the low-rank decomposition $\Delta W = BA$, where $B \in R^{d\times r}$ and $A \in R^{r\times k}$, with the rank $r \ll d$. The objective function is defined as equation (16):

$$L_{MSE} = \frac{1}{N}\sum_{i=1}^{N}\left\| y_i - \left(W_0 x_i + BAx_i\right)\right\|^2 \tag{16}$$

4.1.2 Generation control of edge guidance

In order to overcome the structural randomness of the results generated by the diffusion model, this study introduces the ControlNet control architecture, which realizes the controllability of the design through edge detection and conditional constraints.The core design of ControlNet consists of three key steps, namely, structural feature extraction, zero-convolutional conditional injection, and multiconditional co-generation.

Structural feature extraction is based on the Canny algorithm to detect the edges of the modern boutique theme hotel space and generate contour maps as control conditions.

Zero-convolution condition injection encodes the contour map into a 64×64 feature map, dynamically adjusts the parameters through the convolutional layer with zero initial weight, and fuses the feature map with the diffusion model UNet network layer by layer.

The multiconditional co-generation combines the Hmong semantic features of LoRA module and the structural constraints of ControlNet to drive the diffusion model to generate a design solution that is both culturally recognizable and functional.

By introducing the ControlNet control architecture and combining the LoRA module, this study realizes the edge-guided generation control, effectively overcomes the structural randomness of the diffusion model generation results, and provides a highly efficient and controllable technological path for the innovative design of regional traditional culture.

4.2 Theme hotel space creation design

This section mainly analyzes the design concept of this theme space creation, specifically including the source of the design concept, the extraction of the design concept symbols and the transformation of the design concept symbols. The design concept is developed by the traditional cultural symbols of the region, extracting the cultural symbols therein, and explaining the transformation of the design concept symbols in the space to draw out the more influential cultural values.

(1) Design concept symbol extraction

This theme space creation design starts from symbol extraction, selects representative symbols as the main symbols to be transformed and applied in the space, and combines with plant patterns, animal patterns, and natural object patterns as embellishments for decoration. The curved form of the symbols is extracted and rotated and twisted from line to surface, and the overall flow is rich in coherence.

(2) Design Concept Symbol Transformation

The design concept of this program is “colorful decoration, charismatic symbols”, to create a regional traditional decorative symbols theme space to create a regional cultural symbols and modern technology combined with the regional meaning of the cultural space brand, to achieve colorful regional traditional cultural decorative symbols and modern decorative language of communication. As a cultural place, it displays regional traditional cultural characteristics, and as a spiritual place, it explores the historical value of a specific period.

(3) Design and investigation program

Based on the above design strategy, using this paper's regional traditional cultural symbols extraction and translation (AIGC) model, design a boutique theme hotel space creation results containing traditional regional traditional cultural symbols, and put into use, the use of the hotel is called Hotel 6. 500 tourists were interviewed randomly through random visits and surveys to investigate the use of the theme hotel space creation feelings.

5 Hotel space creation empirical analysis

5.1 Multi-dimensional analysis of regional traditional cultural symbols in hotel space creation

5.1.1 Holistic description of evaluation results

Figure 3 shows the descriptive statistical analysis of space creation in theme hotels, which is divided into five grades, with 1 to 5 indicating very poor, poor, average, good and very good, respectively. In the overall rating, the overall score of typical hotels is 2.95, the rating is close to but not reach the better grade. This indicates that there are still some real problems in the actual use of cultural symbols and practical activities carried out by tourists.Hotel 1 and Hotel 6's theme hotel space creation rating is between better and better, with scores of 3.045 and 3.123 respectively, and especially H6 is ranked the first with a more obvious advantage. The rest of the four boutique theme hotels are average grade, which is located in H3 and H4 score with 2.825 and 2.736 respectively at the end of the list.

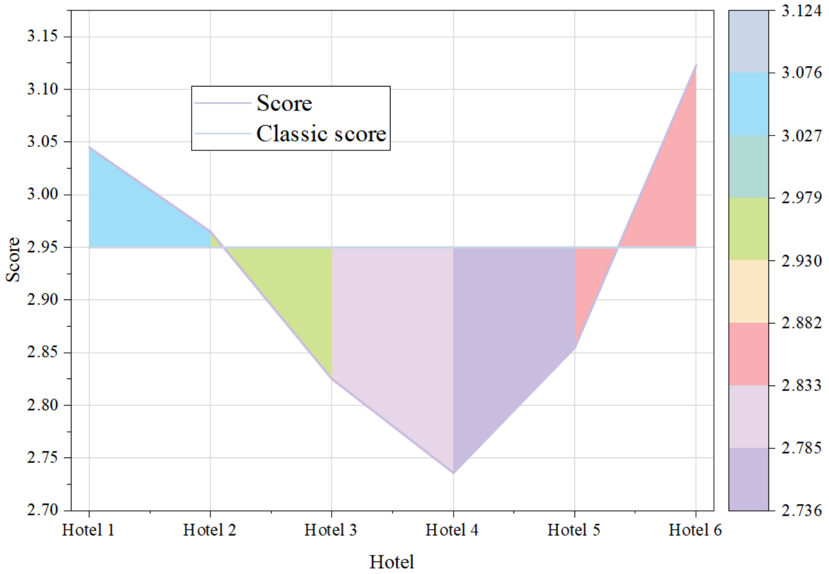

Figure 3: The theme hotel space creates descriptive statistical analysis

Figure 4 shows the spatial cultural feeling characteristics, this paper selected three aspects of cultural development fit (B1), spatial experience feeling characteristics (B2) and cultural participation feeling characteristics (B3) to be analyzed. The overall situation of typical hotels is that B2 has the highest score of spatial experience feeling characteristics, and the rating reaches a better level, and what factors help tourists get a better experience of the cultural scene should be further analyzed, and the score of cultural participation feeling characteristics of B3 (2.602) is significantly lower than that of B1 (2.93) and B2 (3.069), which indicates that cultural symbols have a worse status quo of tourists' participation and activities in the hotel space, and that cultural development fitness (B1) and cultural participation characteristics (B2) are more important than that of B2. In the cultural development fitness, H6 and H1 have scores of 3.017 and 2.897 respectively, which are in the top two and have opened a large gap with the remaining four districts.

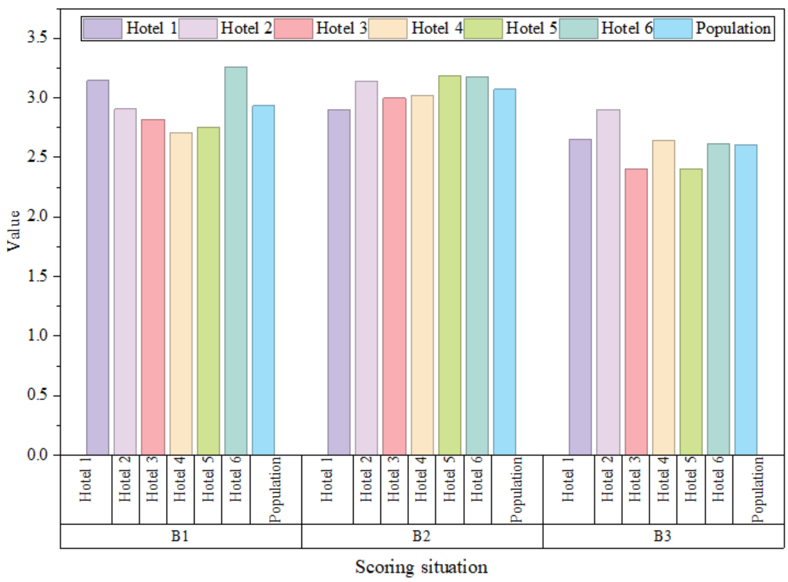

Figure 4: Spatial and cultural characteristics

Figure 5 shows the evaluation of hotel space creation influence factors, and this paper selected six aspects such as space quality (C1) and activity adaptation (C2) as the factor layer to be analyzed. In the overall evaluation of typical hotel space, there is a gap between the scores of C1 spatial quality and C2 activity suitability, indicating that the physical space and facilities may have a certain degree of inactivity or transfer of use, and cultural activities fail to make full use of the hotel's physical resources, while the scores of C3 crowd experience and C4 emotional benefits are higher, with the mean values of 3.05 and 3.162, respectively; however, the differences between different types of hotels are more obvious, indicating that differences such as the age of the hotel and the type of space enclosure may influence the hotel's spatial creation. This indicates that differences such as the age of hotel construction and the type of spatial enclosure may affect the crowd's spatial perception and the closeness of neighborhood interactions, and the C5 cultural vitality and C6 hotel impact scores are obviously low, and some hotels even have poor ratings, indicating that there are certain drawbacks in the hotel's ability to create a distinctive cultural scene, mobilize tourists' spontaneity and organization, and promote the level of common participation in cultural construction.

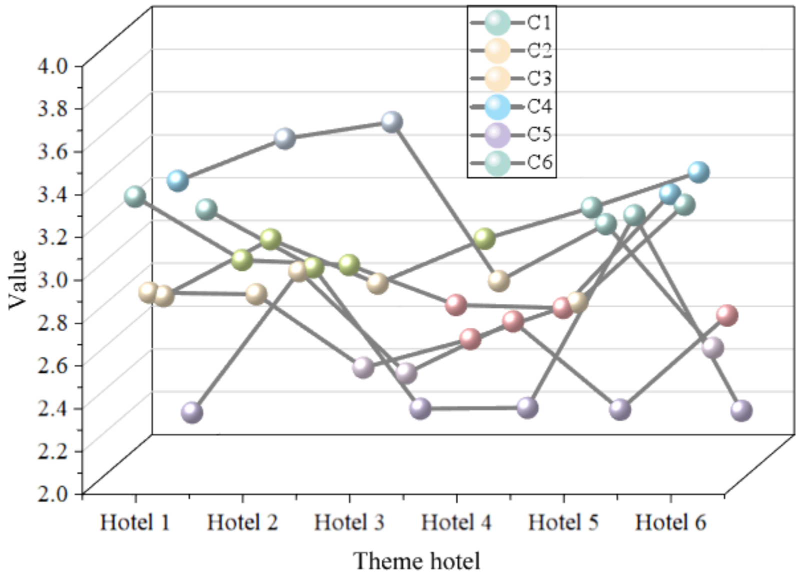

Figure 5: The hotel space creates the influence factor evaluation

5.1.2 Spatial and cultural development suitability

The refinement of the two factors C1 and C2 contains six indicators, which are D1 spatial scale appropriateness, D2 facility perfection, D3 spatial accessibility, D4 management and maintenance level, D5 functional rationality, and D6 spatial development potential, and Fig. 6 shows the degree of appropriateness of spatial and cultural development, and the spatial accessibility ratings of all the hotels are higher, with a mean value of 3.597, which is still spatial development potential.

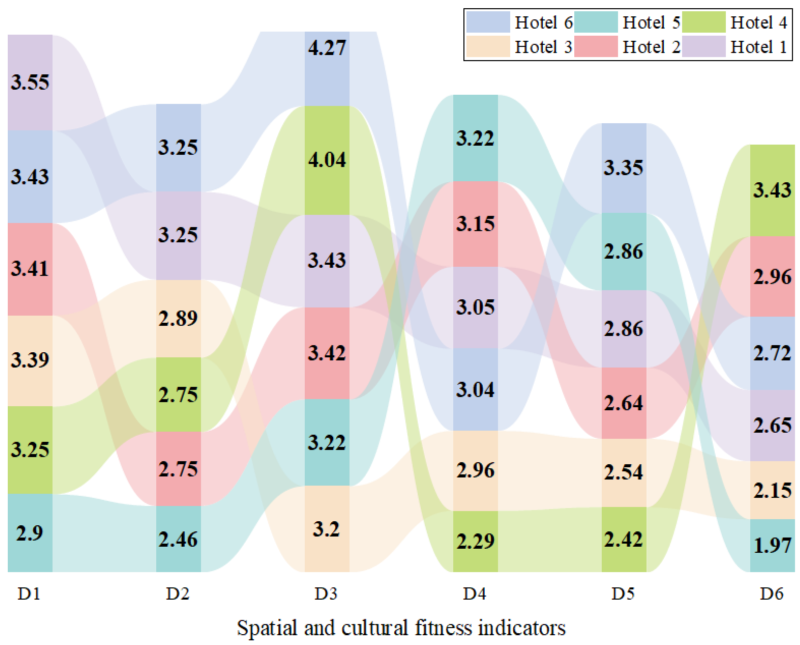

Figure 6: The compatibility between space and cultural development

5.1.3 Sense of visitor experience in the space

The refinement of the two factors C1 and C2 contains five indicators, D7~D11 are space utilization, space richness, environmental comfort, interaction positivity and sense of belonging, respectively. Figure 7 shows the sense of visitors' experience in the space, and after the combination of regional cultural symbols and hotel space creation, D9, D10 and D11 have higher ratings of 3.138, 3.12 and 3.227 respectively.

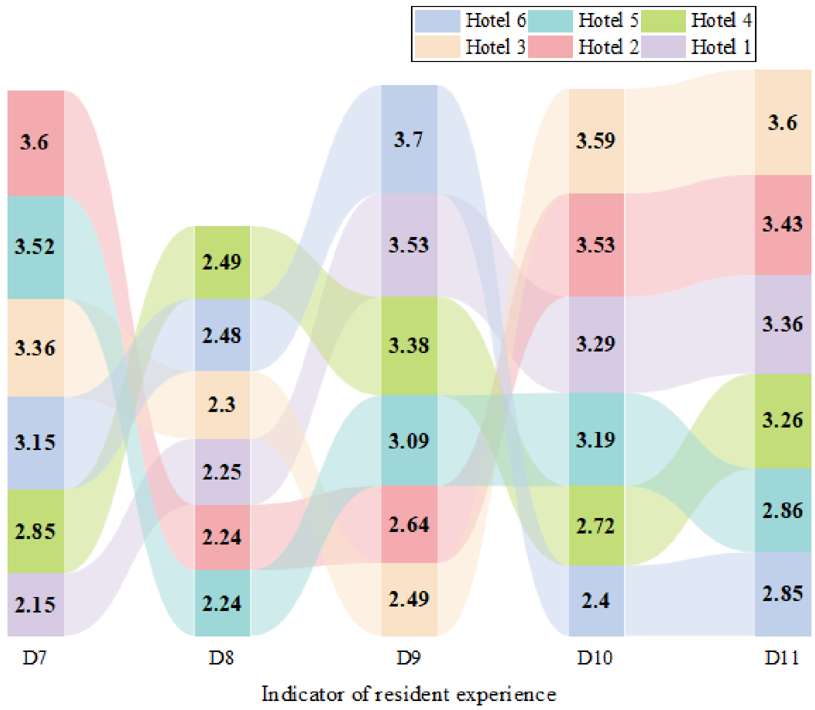

Figure 7: Experience of visitors in space

5.1.4 Tourists' sense of cultural participation

Figure 8 shows the refinement of C5 and C6 indicators, and five indicators were obtained after the refinement, namely, the intensity of cultural activities (D12), the participation in cultural construction (D13), the richness of types of activities (D14), the creation of a cultural atmosphere (D15), and the regional cultural characteristics (D16), of which the richness of types of activities is more prominent, with a score of 2.82, but there is a problem of insufficient creation of regional cultural characteristics.

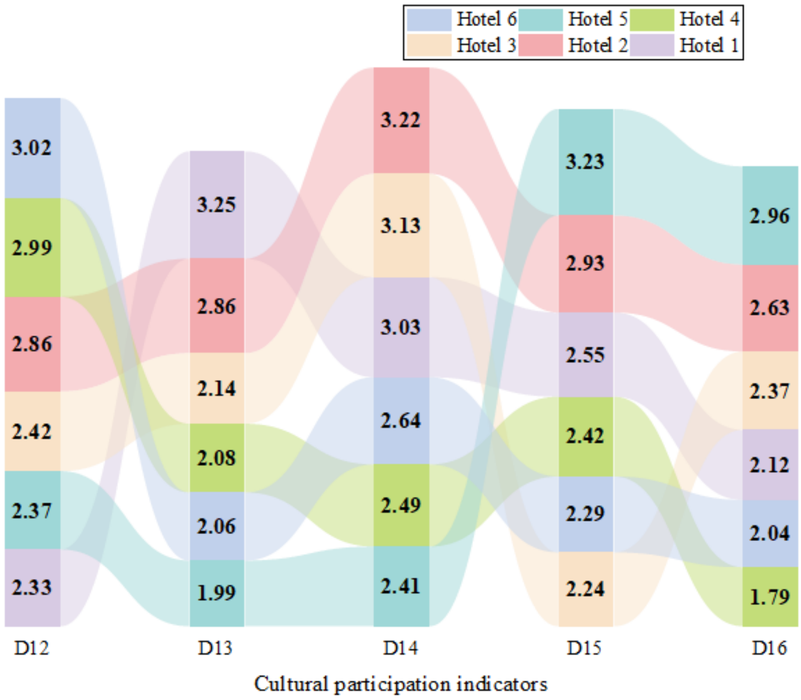

Figure 8: Tourists' sense of cultural participation

5.2 Tourist Satisfaction Analysis

5.2.1 Spatial preferences

According to the degree of preference of visitors, all types of space creation are ranked, and Figure 9 shows the preference of different types of space creation. As the semi-open space has the characteristics of semi-closed and semi-open, it provides visitors with spacious activity space and a certain degree of shade, compared with other spaces, the activity types of semi-open space are more diverse, and visitors have a strong sense of experience and more comfortable psychological feelings, which are favored by all types of people. Therefore, it has the highest space creation score in boutique hotels, and the mean value of space preference is 42.977%.

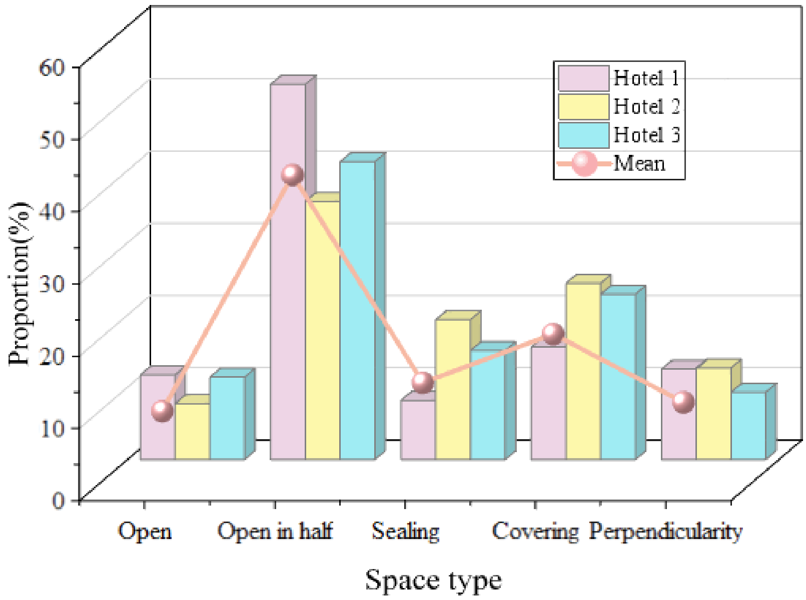

Figure 9: Different types of spatial preferences

5.2.2 Differences in crowd preferences for different types of cultural spaces

Figure 10 shows the difference in crowd preference for different types of hotel space, open regional traditional cultural space has more types of activities, mainly sports, play, square dance, etc., which can meet the needs of the elderly to carry out group activities and exercise, so it is more popular among the elderly, and the degree of preference for those over 60 years of age reaches 23.506%, but due to the large area and the lack of shade, compared to the semi-open space, it lack of comfort and security, thus the overall popularity is lower.

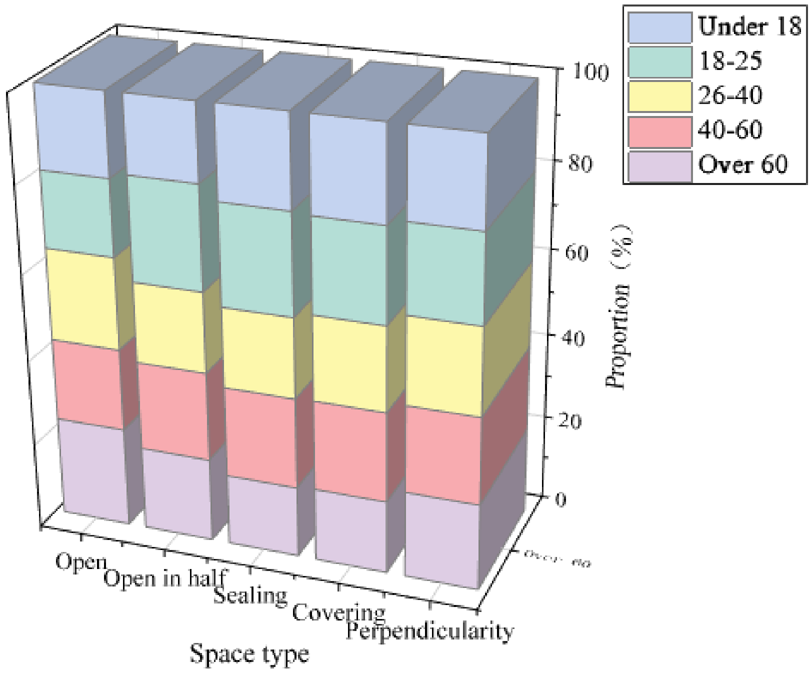

Figure 10: Different types of hotel space preferences are different

5.2.3 Spatial satisfaction

Figure 11 shows the spatial satisfaction of different types of boutique theme hotels. The sample sites of the three research hotels were categorized according to different types of space composition, and the satisfaction of travelers with different types of space was analyzed separately.The hotel space H6 of the boutique theme containing regional traditional cultural symbols designed by using AIGC technology had the highest visitor spatial satisfaction, and the percentage of very satisfied with all the space created reached 43.365%.The most dissatisfied of the travelers in H1 was the closed space, and the satisfaction was less than 70%, followed by covered space, satisfaction is 71.881%, two types of space satisfaction is significantly lower than the other space.H6 different types of space visitor satisfaction from the whole are relatively high, which the highest satisfaction is covered space and open space, satisfaction is around 90%, respectively, 92.267% and 89.45%, satisfaction is relatively low is semi-open space but satisfaction are above 80%, which are more important for H6 and should enhance its cultural landscape space.

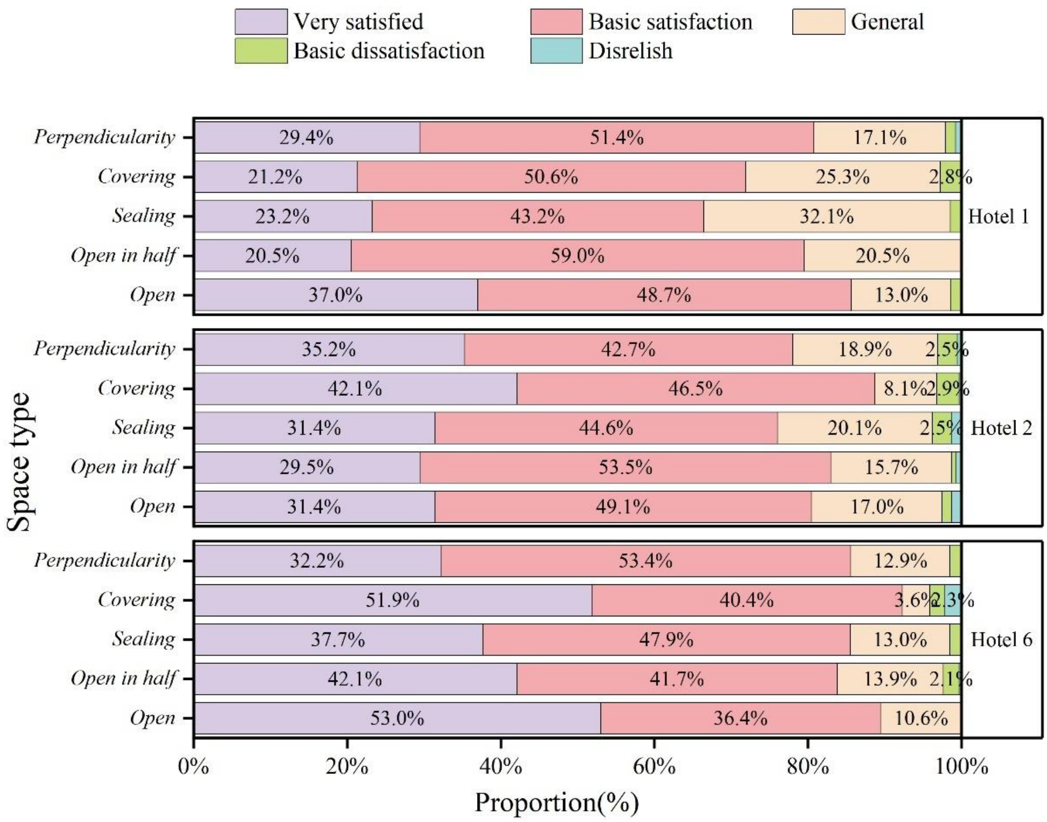

Figure 11: Different types of high-quality hotel space satisfaction

6 Conclusion

In this paper, a three-point strategy is proposed for regional traditional culture symbols translation, according to which CBAM is introduced into the ResNet-50 structure to parse the symbols of regional traditional culture, followed by feature post-processing algorithms to realize feature decoupling, and t-SNE to visualize the distribution of regional style clusters. The cross-modal alignment of visual features and textual semantics is accomplished by the latent space alignment method. The LoRA model is used to fine-tune the parameters on the basis of Stable Diffusion diffusion probability model to train the model with regional cultural symbol style. The model is put into the space creation design of theme hotels to elicit more influential cultural values. The overall score of the space creation effect of all theme hotels is 2.95, and the H6 hotel, which utilizes the method of this paper for the design of hotel space creation, has the highest score of 3.123. According to the degree of preference of tourists, the various types of space creation are sorted, and the highest in the space creation score of boutique hotels, the average value of space preference is 42.977%. Meanwhile, the satisfaction of all types of space in H6 is above 80%, and its cultural landscape space should be further enhanced.

About the Author

Yichao Wu was born in Shaoxing, Zhejiang, P.R. China, in 1997. He obtained a PhD degree from Woosong University in South Korea. I am currently teaching at the School of Hospitality Management, Zhejiang Yuexiu University. My main research direction is hospitality management related.

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