

Data-Driven Color Palette Optimization for Interior Decoration: A Decision-Support Framework Based on Cluster Analysis and Emotional Needs Mapping

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Abstract: The color selection in interior decoration design is based on the subjective aesthetic of the designer, but this can result in low design efficiency and difficulty in considering human emotional needs. To address these issues, this study proposes an objective design-assistance method based on K-means clustering in color space. The method first systematically collects real indoor scene image samples, then extracts high-dimensional features such as color matrices and color histograms from two color modes. Finally, the K-means algorithm automatically categorizes samples based on color characteristics and then correlates them with latent emotional needs. The results indicated that color space conversion can be achieved for different indoor scenes. In a one-way analysis of variance, the p-values for calm, exciting, cool and warm across different emotional needs are all less than 0.001. Therefore, the color space clustering results are applicable, and designs that consider emotional needs are practical. This method can automatically identify effective color designs from design cases, and its results can provide quantifiable color references for interior decoration with different emotional orientations.

Keywords: Interior decoration; cluster analysis; emotional needs, lab color; practical color coordinate system (PCCS).

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1. Introduction

Currently, color in interior design is a major factor affecting users emotions. With continuous improvements in socio-economic levels and increasing emphasis on emotional resonance and expression, the focus of interior has shifted toward the Emotional Need (EN) level (Sabha and Saffarini, 2024). Color can affect people's emotions and psychological responses in interior design and, to some extent, regulate spatial perception, playing an important role in enhancing the aesthetic and functional aspects of the environment (Rong, 2024). Given the high efficiency of rapidly developing information technology, linking color design with EN as a decision-making basis for design has become one of the urgent problems to be solved (Gao and Liang, 2025). However, traditional design practices often rely on designers' subjective experience and emotional judgment. Although there is certainly some creativity involved, there is actually no systematic data support. This lacks specificity and accuracy for people's diverse individual needs (Lu, 2025).

In the fields of color feature analysis, image processing, and data clustering, numerous scholars have employed K-means and its optimized algorithms for analysis. Among these, Feng et al. (2024) utilized the K-means clustering algorithm and the SD semantic difference method to quantify landscape color characteristics and human perception across different parks and seasons. The results demonstrated the feasibility of this approach. Xu (2024) developed a color design model that integrates particle swarm optimization-enhanced K-means clustering and simulated annealing to enable adaptive lighting adjustments, thereby enhancing efficiency and accuracy in indoor scene color design. Results indicated that this method yielded optimal F-values. Weng et al. (2025) analyzed images using the DeepLab V3 model and the K-means clustering algorithm to address inconsistencies in color representation between street-view images and pedestrian-perspective images in rural environments. Results demonstrated the method's accuracy. Cai et al. (2024) proposed a novel multi-view fuzzy C-means clustering algorithm to better preserve image detail information. This algorithm automatically adjusted view weights, integrated local spatial and grayscale information, and employed kernel-based distance metrics to improve robustness to noise. Results demonstrated its accuracy and robustness. Zhu et al. (2024) enhanced unsupervised fuzzy K-means clustering by incorporating labeled information through dynamic adjustment and label-discrimination mechanisms, thereby improving clustering performance and stability. Results indicated the method exhibited noise resistance.

Some professionals employ multiple smart technologies in interior design to enhance efficiency. For instance, Shi et al. (2025) analyzed the full life-cycle carbon emissions and economic viability of prefabricated interior finishes by constructing a dynamic environmental life-cycle cost model. Results indicated that prefabricated interior finishes could reduce carbon emissions by 187.58 kg CO₂-eq/m². Chen et al. (2024) proposed a reverse design method based on a parametric level set approach to design indoor environmental control models, incorporating K-means clustering for terminal shape regularization. Results demonstrated that this method reduced the mean absolute error to 0.102. Zhou (2025) developed a web-based interactive Virtual Reality (VR) collaborative display system for interior design, integrating mobile panoramic stitching technology to enable network sharing and transmission of 3D model data. Results indicated the system achieved an average computation time of 12.19 seconds. Zhang and Wang (2024) enhanced user experience by introducing an attention mechanism to optimize the CenterNet algorithm, combining long short-term memory networks with convolutional neural networks to construct an interior space design recognition system. Results indicated the system's high efficiency. Zhou (2024) addressed architectural decoration design and production by integrating VR technology with weight analysis to determine design sequences for different decorative elements. Findings revealed that spatial functionality carried the highest weight, reaching 21.55×10^{-2} .

In summary, existing studies have attempted to introduce computational methods for color extraction. However, existing research has failed to comprehensively assess the representational power of different color spaces, and the exploration of statistical features, such as color distribution, remains insufficient. This will result in analysis results that cannot efficiently and comprehensively reflect people's needs and emotional experiences for the overall color of the space. To address this, the study innovatively integrates color space theory from machine vision with the K-means clustering algorithm into the design analysis workflow. By fusing multidimensional color features with real-world scene image data, it constructs a data-driven color-emotion mapping model.

2. Methodology

2.1. Image Dataset Construction and Color Feature Extraction

2.1.1. Image source and preprocessing

All images used in this study were sourced from colorhub.me, and 1200 images were collected and screened. Images cover diverse styles and various spatial types. To facilitate interior design, the study established an image sample library featuring emotional tags. This study categorized styles into eight distinct types: American Country, Classical European, Mediterranean, Southeast Asian, Japanese, Neoclassical, Modern Minimalist, and New Chinese (Sawatmongkhonkul et al., 2024). To ensure diversity of styles, all images were layered into 8 interior design styles, with 150 images per style. This study used an open-source Python preprocessing script to completely record the core parameters of image preprocessing. The image size was uniformly adjusted to 512×512 pixels. Color correction used the gray world algorithm to achieve white balance, and the gamma value was set to 2.2. Image selection criteria require clear, well-lit images. Images undergo size standardization, cropping, and color correction to reduce noise in subsequent analysis. Examples of interior design images are shown in Fig. 1.



Fig. 1. Interior design image samples (Source: (a) <https://www.colorhub.me/photos/4jdWG>; (b) <https://www.colorhub.me/photos/VwwDJ>; (c) <https://www.colorhub.me/photos/JPVvk>; (d) <https://www.colorhub.me/photos/voarX>)

2.1.2. Color space conversion and feature extraction

The Red Green Blue (RGB) color model is an industry-standard color representation widely used in display devices such as televisions, computer monitors, and mobile phone screens, as well as in digital image processing. Its core principle involves generating rich colors by superimposing red, green, and blue light. In interior design, given human visual perception, directly using the RGB color model is not conducive to analysis. This is because it does not align with the human eye's inherent color-perception mechanism (Agbesi et al., 2025). Therefore, it is necessary to convert the image to a color space more suitable for feature extraction. This study used two color spaces, namely Hue Saturation Value (HSV) and lab, to capture color features that more closely align with human visual perception and EN. The conversion algorithm from RGB to HSV color space is shown in Eq. (1).

$$\begin{cases} T_{\max} = \max(R', G', B') \\ T_{\min} = \min(R', G', B') \\ \Delta = T_{\max} - T_{\min} \end{cases} \quad (1)$$

In Eq. (1), $T_{\max}$ and $T_{\min}$ denote the maximum and minimum values among the normalized values R' , G' , and B' , respectively. R' , G' , and B' represent the normalized values of the RGB color channels. The relationship between hue and H is shown in Eq. (2).

$$H = \begin{cases} 0^\circ, & T_{\max} = 0 \\ 60^\circ \times \left(\frac{G' - B'}{\Delta} \right), & T_{\max} = R', G' \geq B' \\ 60^\circ \times \left(\frac{G' - B'}{\Delta} + 6 \right), & T_{\max} = R', G' < B' \\ 60^\circ \times \left(\frac{B' - R'}{\Delta} + 2 \right), & T_{\max} = G' \\ 60^\circ \times \left(\frac{B' - R'}{\Delta} + 4 \right), & T_{\max} = B' \end{cases} \quad (2)$$

The relationship between saturation S and brightness V is shown in Eq. (3).

$$S = \begin{cases} 0, & T_{\max} = 0 \\ \frac{\Delta}{T_{\max}}, & T_{\max} \neq 0 \end{cases}, \quad V = T_{\max} \quad (3)$$

The lab color space is the color model that most closely aligns with human visual perception. It provides greater accuracy than RGB for measuring color differences and performing color classification, both of which are highly correlated with emotional perception. Converting from RGB to lab requires using the XYZ color space. The conversion formula for transforming RGB to XYZ is given by Eq. (4).

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.4124 & 0.3575 & 0.1804 \\ 0.2126 & 0.7151 & 0.0721 \\ 0.0193 & 0.1191 & 0.9502 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (4)$$

In Eq. (4), $\begin{bmatrix} X \\ Y \\ Z \end{bmatrix}$ represents the three component values obtained after conversion in the XYZ color space, serving as an

intermediate result in the transformation from RGB to XYZ color space. $\begin{bmatrix} R \\ G \\ B \end{bmatrix}$ denotes the R, G, and B component values in the RGB color space, constituting the input color information. The formula for converting XYZ to lab is shown in Eq. (5).

$$\begin{cases} L = 116 \left(\frac{Y}{Y'} \right) - 16 \\ a = 500 \left[F \left(\frac{X}{X'} \right) - F \left(\frac{Y}{Y'} \right) \right] \\ b = 500 \left[F \left(\frac{Y}{Y'} \right) - F \left(\frac{Z}{Z'} \right) \right] \end{cases} \quad (5)$$

In Eq. (5), X , Y , and Z denote the XYZ components in the XYZ color space, respectively. X' , Y' , and Z' denote the XYZ values of the reference white under standard illuminant conditions, respectively. $F(\cdot)$ represents a nonlinear function, as shown in Eq. (6).

$$F(i) = \begin{cases} i^{\frac{1}{3}}, & i > \left(\frac{6}{29} \right)^3 \\ \frac{1}{3} \left(\frac{29}{6} \right)^2 i + \frac{4}{29}, & \text{other} \end{cases} \quad (6)$$

In Eq. (6), i represents the input parameter of the function. This piecewise nonlinear transformation is designed to make the color space representation better align with the visual perception characteristics of the human eye. The study selects the mean λ_q and variance ρ_q of colors to analyze the color features of interior decoration images, as shown in Eq. (7).

$$\lambda_q = \frac{1}{C} \sum_{d=1}^C p_{q,d}, \quad \rho_q = \left(\frac{1}{C} \sum_{d=1}^C (p_{q,d} - \lambda_q)^2 \right)^{\frac{1}{2}}, \quad t_q = \left(\frac{1}{C} \sum_{d=1}^C (p_{q,d} - \lambda_q)^3 \right)^{\frac{1}{3}} \quad (7)$$

In Eq. (7), C denotes the total number of pixels involved in the calculation. $p_{q,d}$ represents the pixel value at coordinate (q,d) in the image. t_q is the third-order moment of the image color, used to describe the symmetry of the image's color distribution. Schematic diagrams of the HSV and lab color spaces are shown in Fig. 2. In Fig. 2(a), the HSV color space is commonly represented by an inverted cone. The angle of the circle on the horizontal plane is denoted by H. Among them, the chromaticity values for red, green, and blue are 0° , 12° , and 240° , respectively. The dashed line on the horizontal plane represents S. S denotes the purity or vividness of a color, with values increasing as one moves away from the center of the circle. Its range spans from 0 to 255. The vertical dashed line represents V, which signifies the brightness or intensity of a color. A V value of 0 corresponds to black, while a V value of 1 corresponds to white. Value influences perceptions of brightness, oppression, and other spatial qualities. In Fig. 2(b), the lab color space is a color-opposite space. The dimension L represents luminance. Dimensions a and b represent color opposition axes. Dimension a is the red-green axis. Dimension b is the yellow-blue axis. The lab outperforms RGB and HSV in measuring color similarity and distinguishing subtle color differences.

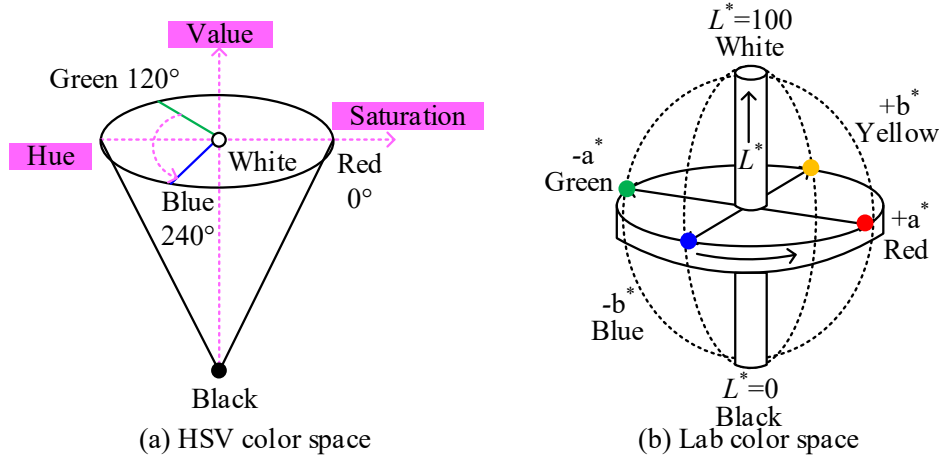


Fig. 2. Schematic diagram of HSV and lab color spaces

2.2. K-Means-Based Color Clustering and Sentiment Mapping

2.2.1. Emotional labeling process

This study conducted a standardized emotional annotation process to achieve an accurate mapping between color clusters and human EN. A total of 12 taggers with professional backgrounds in interior design or psychology were invited to participate in the tagging work. These taggers all received 2 days of special training in color-emotion cognition to ensure they developed a relatively unified framework for understanding the relationship between color and emotion. Combined with the EN of interior decoration design, emotion is divided into five core emotions (EN1-EN5). In the annotation process, the annotator needs to match the most appropriate emotion category for each image based on the visual characteristics of its color cluster, such as the main tone, lightness, purity and so on. Cohen's kappa coefficient was used to quantitatively evaluate and verify annotation consistency.

2.2.2. Extraction of main color clusters based on K-means

After emotional labeling, the study achieves color induction using the K-means clustering algorithm. Since interior decoration design images typically contain multiple colors, analyzing each color individually is inefficient and makes it difficult to summarize people's actual EN. Therefore, this study directly applied K-means clustering to all pixels in the image, without using color pooling or any regional feature aggregation. Global pixel clustering can fully preserve an image's color distribution, avoiding additional bias or information loss from region partitioning or pooling operations. It can more realistically reflect the overall color and emotional characteristics of interior design scenes, and under the existing method framework, this study does not require the introduction of semantic segmentation or region proposal modules. The K-means approach automatically extracts the most representative primary colors from an interior decoration design image. These primary colors serve as a generalized representation of the image's color composition, simplifying the analysis process by categorizing countless hues into a finite number of clusters, each represented by a central color. To map colors to emotions, the study employs the Practical Color Coordinate System (PCCS) to provide a standardized expression of EN that accounts

for human psychological perception of the numerical color results obtained through K-means clustering (Riskiawan et al., 2024). The workflow of K-means and the PCCS hue map are shown in Fig. 3.

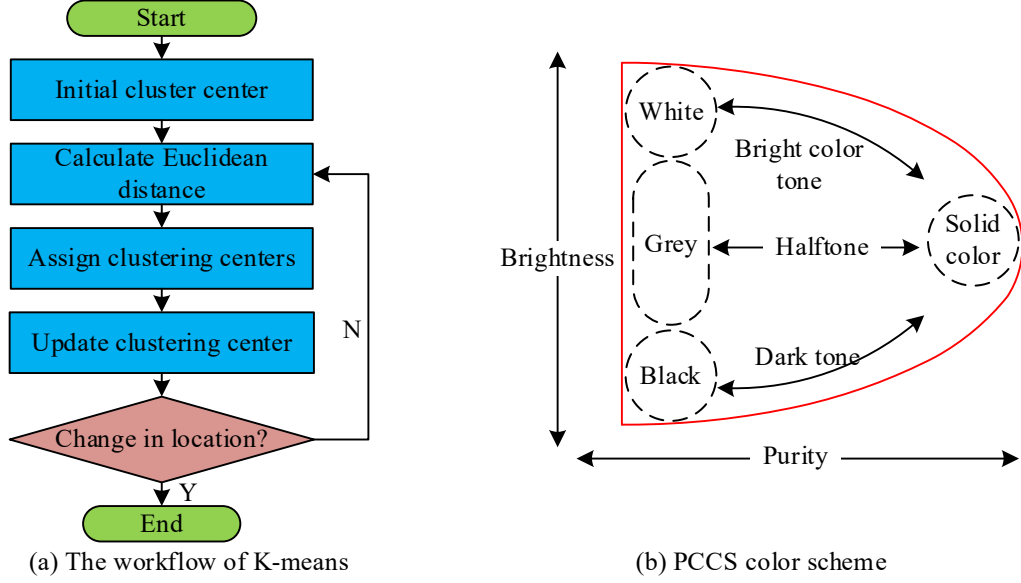


Fig. 3. The workflow of K-means and PCCS color scheme

In Fig. 3(a), the K-means algorithm iteratively assigns all data points, i.e., the lab or HSV values of each pixel, into K clusters. This process aims to maximize similarity among data points within each cluster while minimizing similarity between data points across different clusters. K data points are randomly selected as initial cluster centers, with the value of K requiring prior specification. Subsequently, the color distance from each pixel's color value to every cluster center is computed. Each pixel is assigned to the nearest cluster center based on the nearest-neighbor principle. All pixels assigned to the same center form a cluster. After all pixels are assigned, the cluster centers are recalculated. The new center is typically the average color value of all pixels within that cluster. This reassignment and center update process is repeated until the positions of the cluster centers no longer change significantly. CIEDE2000 (ΔE_{00}) is designed for small color differences and has a relatively high computational cost. In interior decoration design, color variations are significant, and using Euclidean can achieve the best balance between perceptual accuracy and computational efficiency. Therefore, during the assignment, the distance between each data point and all cluster centers is calculated using Euclidean distance d , as shown in Eq. (8).

$$d(p_{\text{data}}, c_{\text{clu}}) = \sqrt{\sum_{i=1}^{N_d} (p_{\text{data}}^i - c_{\text{clu}}^i)^2} \quad (8)$$

In Eq. (8), p_{data} represents one of the data points. c_{clu} denotes a cluster center, and N_d indicates the number of feature dimensions. p_{data}^i and c_{clu}^i denote the values of vectors p_{data} and c_{clu} in the i th dimension, respectively. During the update, the new center c_{new} for each cluster is calculated. The new center is defined as the arithmetic mean of all data points in that cluster across all dimensions. c_{new} is shown in Eq. (9).

$$c_{\text{new}} = \frac{1}{|S_{\text{now}}|} \sum_{p_{\text{data}} \in S_{\text{now}}} p_{\text{data}} \quad (9)$$

In Eq. (9), c_{new} represents the updated new cluster center. S_{now} denotes the set of all data points assigned to this cluster in the current iteration. $|S_{\text{now}}|$ is the size of set S_{now} , i.e., the number of data points belonging to this cluster. $\sum_{p_{\text{data}} \in S_{\text{now}}} p_{\text{data}}$ indicates the summation of the vectors for all data points in the set. To determine its K value, the contour coefficient method is employed. The contour coefficient $C(j)$ for sample s_j is given by Eq. (10).

$$C(j) = \frac{E(j) - I(j)}{\max\{I(j), E(j)\}} \quad (10)$$

In Eq. (10), $I(j)$ represents the average distance between s_j and all other samples within the same cluster, reflecting the compactness of samples within their own cluster. The smaller $I(j)$ is, the tighter the samples are within their own cluster. $E(j)$ is the average distance between s_j and all samples in the nearest other cluster, indicating the degree of separation between the sample and other clusters. The larger $E(j)$ is, the more separated the sample is from other clusters. The average distance between s_j and all samples in the nearest set G_m is calculated, where G_m is defined by Eq. (11).

$$G_m = \arg \min_{G_n} \frac{1}{Z} \sum_{A \in G_n} |A - s_j|^2 \quad (11)$$

In Eq. (11), Z and A denote the number of samples and sample points within cluster G_n , respectively. The internal metric Sum of Squared Error (SSE) in cluster analysis can be used to evaluate clustering effectiveness and measure the compactness within clusters. SSE is defined in Eq. (12).

$$\text{SSE} = \sum_{k=1}^K \sum_{p_{\text{data}} \in G_n} \|p_{\text{data}} - c_{\text{clu}}\|^2 \quad (12)$$

In Eq. (12), K represents the number of clusters.

2.2.3. Color emotion mapping based on PCCS

After emotion annotation and extraction of main color clusters, this study further establishes a standardized mapping from color features to ENs using the PCCS color coordinate system. Fig. 3(b) illustrates the interrelationships and transitions between different color types and hues within the PCCS color system, based on the two dimensions of lightness and chroma. Its hue wheel is built upon six primary colors, red, orange, yellow, green, blue, and violet, from which 24 sub-hues are derived and digitally coded. The lightness axis spans nine stages from 1.0 to 9.5, while purity is denoted by S with independent benchmarks for each hue (Shoukat et al., 2024). Table 1 shows the correspondence between PCCS basic tones and EN.

Table 1. PCCS basic color tone and EN correspondence table

Hue	Main emotional keyword	Associated EN
Red tone	Enthusiasm, excitement, danger, celebration	Warm, energy (EN1)
Blue tone	Calm, rational, quiet, melancholy	Calm, peaceful (EN2)
Yellow tone	Brightness, happiness, hope, anxiety	Warmth, joy (EN3)
Green tone	Nature, peace, growth, security	Relax, unwind (EN4)
Purple tone	Noble, mysterious, elegant, lonely	Luxury, artistry (EN5)

To facilitate image analysis, the study employs Adobe Photoshop 2025 v26.9.0.15 for image processing, using modern minimalist, American country, and Japanese styles as examples. Fig. 4 compares images before and after processing for three different styles. Figs. 4(a) through (c) show the original images of three different styles. Fig. 4(d) through (f) are color block diagrams of the corresponding styles. This process segments the original image's colors, transforming the rich, naturally transitioning hues into relatively regular color blocks.

3. Results and Analysis

3.1. Clustering Results for Interior Decoration Design

This study set the key hyperparameters of the K-means algorithm to ensure the stability and reproducibility of the clustering process. The initialization strategy was K-means++, with ten repeated runs, a maximum of 300 iterations, and a random seed of 42. Color quantization was not performed, and the original pixel values in the lab color space were used directly as input for clustering.



Fig. 4. Original image and color block diagram in modern style (Source: (a) <https://www.colorhub.me/photos/GyR9N>; (b) <https://www.colorhub.me/photos/vqeyD>; (c) <https://www.colorhub.me/photos/KgAw9>)

Fig. 5 illustrates the relationship between the contour coefficient and SSE for different cluster numbers K in interior decoration clustering analysis. In Fig. 5(a), as K varies, the contour coefficient initially showed a fluctuating upward trend. When K was around 5, the contour coefficient reached a relatively high value of 0.026. When K continued to increase to 10, the contour coefficient dropped significantly to 0.006. In the interior decoration clustering analysis, an optimal K value existed near 5, where clustering performance was relatively good. In Fig. 5(b), the error decreased significantly when K ranged from 1 to 5, and the SSE remained stable between 5 and 10. When K was set to 5, the SSE was approximately 1.5×10^{-8} . To overcome the limitations of purely data-driven approaches, this study integrated the contour coefficient method, SSE, and EN classification to ultimately categorize sentiment themes into five classes. Therefore, K was set to 5.

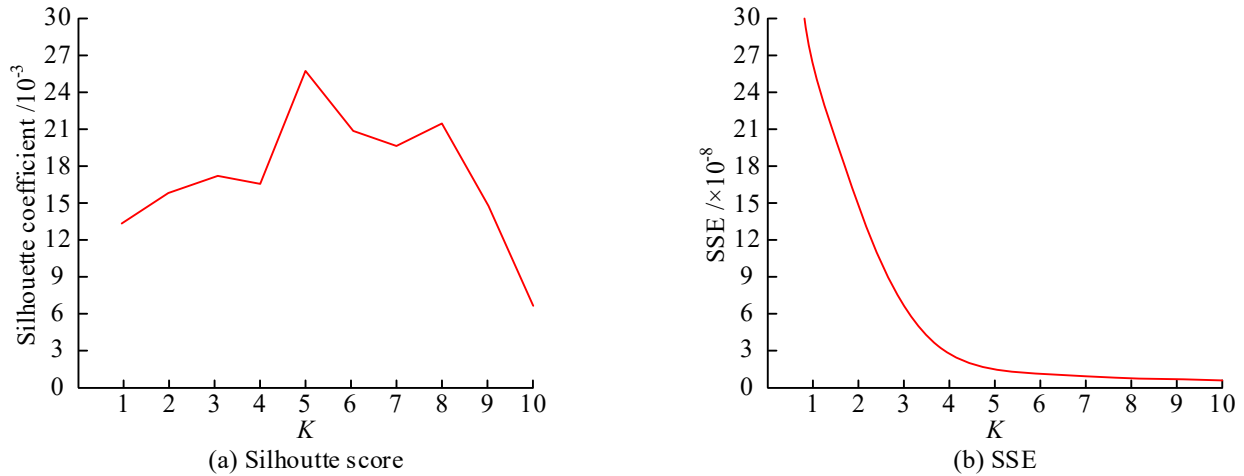


Fig. 5. Silhouette coefficient and SSE variation results

The color space conversion results for the hex color codes provided in scenes 1-4 are shown in Table 2. Table 2 presents the color conversion outcomes for scenes 1-4. For these four scenarios, the numerical correspondence in different color spaces confirmed the effectiveness of the color space conversion process, providing a basis for subsequent EN mapping.

The RGB, HSV, and lab color space histograms for the sofa in indoor scene 1 are shown in Fig. 6. Fig. 6(a) displays the RGB histogram for the light blue sofa. The pixel distribution peak for channel B reached 7.6×10^4 , the highest value. Given the sofa's light blue color, the pixel peaks in the R and G channels were relatively low. Fig. 6(b) shows the HSV distribution of this sofa. Among them, the peak value of the H channel was 5.5×10^5 . The meaning was that the sofa's color fell within the blue spectral range. The peak value of the S channel was only 1.9×10^5 , indicating low color saturation and a lack of bright colors. The peak value of the V channel was 3.3×10^5 , indicating high brightness. In Fig. 6(c), the peak value of the L channel for this color was 6.3×10^5 . The pixel distribution of channel A did not show a significant peak, indicating that this color would not exhibit a noticeable red or green bias. The peak value of channel B was 4.5×10^5 . This directly reflected the color's bias towards blue tones.

Table 2. Color conversion results for scenes 1-4

Scene type	Hex	RGB	HSV	Lab
Scene 1	#c5c1bd	(197, 193, 189)	(30°, 4%, 77%)	(78.6, 0.3, 3.1)
	#281e1e	(40, 30, 30)	(0°, 25%, 16%)	(13.3, 4.3, 1.8)
	#793e24	(121, 62, 36)	(18°, 70%, 47%)	(32.5, 23.4, 26.8)
	#9b6f44	(155, 111, 68)	(30°, 56%, 61%)	(49.4, 11.3, 29.4)
	#76757a	(118, 117, 122)	(253°, 4%, 48%)	(49.3, 1.6, -2.5)
Scene 2	#d3d1ce	(211, 209, 206)	(36°, 2%, 83%)	(83.8, 0.2, 2.4)
	#4f575b	(79, 87, 91)	(201°, 13%, 36%)	(35.9, -2.9, -4.8)
	#ab754e	(171, 117, 78)	(24°, 54%, 67%)	(53.4, 15.3, 29.9)
	#788292	(120, 130, 146)	(218°, 18%, 57%)	(53.8, -2.7, -10.9)
	#656370	(101, 99, 112)	(248°, 12%, 44%)	(42.7, 4.5, -8.7)
Scene 3	#bba38a	(187, 163, 138)	(30°, 26%, 73%)	(68.7, 5.4, 16.3)
	#342317	(52, 35, 23)	(25°, 56%, 20%)	(16.4, 6.4, 14.1)
	#773d15	(119, 61, 21)	(24°, 82%, 47%)	(31.6, 22.4, 31.4)
	#b26e2b	(178, 110, 43)	(30°, 76%, 70%)	(52.4, 22.4, 50.3)
	#d9dcde	(217, 220, 222)	(206°, 2%, 87%)	(87.5, -0.9, 0.1)
Scene 4	#ddd6ce	(221, 214, 206)	(30°, 7%, 87%)	(85.2, 1.5, 5.8)
	#efcecl	(239, 236, 225)	(47°, 6%, 94%)	(93.1, -0.8, 6.9)
	#c5bdba	(197, 189, 186)	(16°, 6%, 77%)	(77.3, 2.7, 3.2)
	#b4a38e	(180, 163, 142)	(33°, 21%, 71%)	(67.8, 4.2, 14.1)
	#7f706e	(127, 112, 110)	(7°, 13%, 50%)	(48.2, 5.6, 3.9)

3.2. Interior Decoration Design Style, Color, and Spatial Clustering Analysis with EN Analysis

The color proportions in scenes 1-4 are shown in Fig. 7. In Fig. 7(a), the light shade #c5c1bd accounts for approximately 64.5% of scene 1, creating an overall fresh and tranquil mood. In Fig. 7(b), the proportions of #4f575b and #788292 in scene 2 exceed 40%, at 45.5% and 41.0%, respectively. The overall design expresses interior decoration through sophisticated, substantial, and composed elements. In Fig. 7(c), the proportion of #b26e2b in scene 3 is approximately 60.5%, belonging to the warm color spectrum, effectively fulfilling people's need for warmth. In Fig. 7(d), the dominant color tone in scene 4 was light, and #ddd6ce (warm beige) accounted for the largest share, exceeding 40%. This created a different EN for residents who prefer a clean, minimalist style.

For modern minimalist style, the clustering analysis results of five EN types are shown in Fig. 8. In Fig. 8(a), when considering mean and variance, the image clusters corresponding to the five EN types exhibited differences in scale. EN2 and EN3 had the largest sample sizes, with 367 and 315 samples, respectively. The sample size for EN5 was only 100, the smallest among the samples. The point group of EN1 was distributed between EN3 and EN2. It had warm, bright color characteristics consistent with the description of high-saturation warm tones in PCCS. In Fig. 8(b), clustering analysis that considered only the meaning showed that EN1 and EN5 were distributed in completely different regions of space. The difference in warm and cool tones between the two was significant.

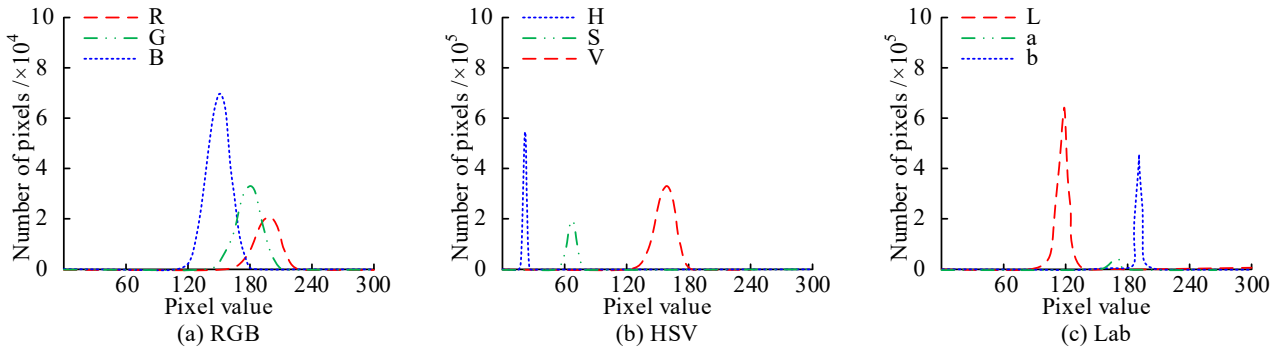


Fig. 6. RGB, HSV, and lab color space color histograms of sofa in scene 1

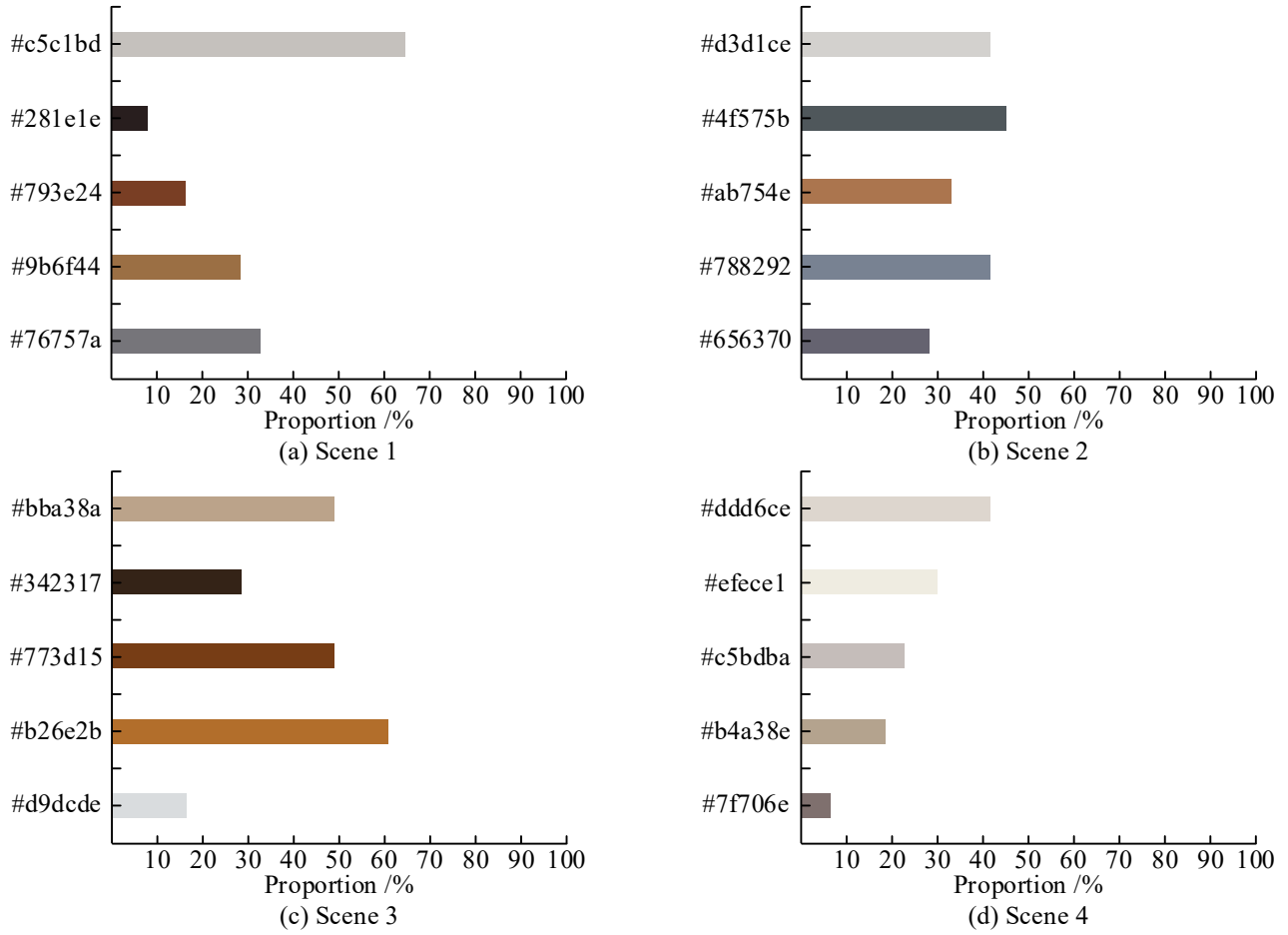


Fig. 7. Color proportion in scene 1-4

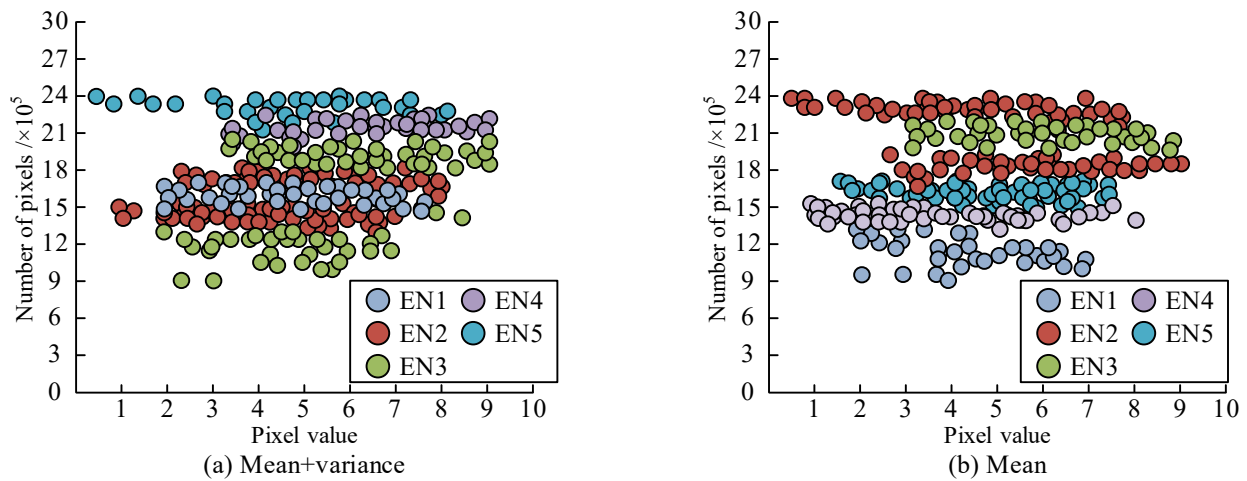


Fig. 8. Cluster analysis results of five types of EN

The K-means clustering results for the modern minimalist, American country, and Japanese styles are shown in Table 3. The L range of modern minimalist style was between 25 and 80, with a large brightness range. The range of A was 2-15, and overall, this style tended to be warm. B ranged from 4 to 30 and had a distinctly warm color. According to the lab, the overall saturation of the American country style was high, and the warm colors were strong. The colors of Japanese style were mainly light-colored, with high brightness and low saturation, and overall, a neutral warm tone.

Table 3. Three styles of K-means clustering calculation results

Interior design style	Cluster number	L, a, b*	Representative RGB color	Number of samples within clusters
Modern minimalist	1	(80, 2, 8)	#cabdb3	150
	2	(25, 2, 4)	#3d3430	120
	3	(55, 5, 12)	#8b796d	95
	4	(55, 10, 30)	#95734b	80
	5	(35, 15, 25)	#744b37	45
American country	1	(75, 8, 22)	#1f0c06	140
	2	(45, 18, 35)	#5f2a18	120
	3	(65, 12, 40)	#bbb09d	100
	4	(55, 22, 45)	#9a6a42	85
	5	(70, 5, 30)	#f3cd84	60
Japanese style	1	(85, 2, 8)	#d2ccc1	160
	2	(75, 5, 12)	#b9aa97	130
	3	(65, 8, 15)	#a79178	105
	4	(50, 3, 8)	#937657	75
	5	(80, 0, 5)	#3d3229	50

3.3. Subjective Validity Verification

To verify whether the proposed method could effectively evoke expected emotional responses, this study conducted a pilot perception study. The study selected 15 representative color palettes and corresponding indoor scene diagrams from 5 types of ENs. 50 participants with normal color vision participated in this test. The study selected a 7-point Likert scale to evaluate two core emotional dimensions: calm (1)-exciting (7), cool (1)-warm (7). The subjective perception score and Analysis of Variance (ANOVA) results are shown in Table 4.

In Table 4, the single-factor ANOVA results showed that the color schemes for different EN categories had a calm–excitement result of $F=18.62$, $p<0.001$, biased $\eta^2=0.32$. The cool–warm arm result was $F=22.35$, $p<0.001$, biased by $\eta^2=0.38$. There were significant differences in both dimensions. This indicated that participants were able to clearly distinguish the emotional traits conveyed by different color schemes.

Table 4. Subjective perception score and ANOVA results

EN category	Calm–exciting		Cool–warm	
	Mean	SD	Mean	SD
EN1	5.82	0.85	6.15	0.72
EN2	2.15	0.68	1.92	0.63
EN3	5.31	0.91	5.88	0.8
EN4	2.46	0.73	3.12	0.77
EN5	4.28	0.88	4.05	0.91
ANOVA Results	$F(4, 145) = 18.62$		$F(4, 145) = 22.35$	
<i>p</i> -value	<0.001		<0.001	
Effect size (Deviation from η^2)	0.32		0.38	

3.4. Code Availability and Reproducibility

The complete script pipeline workflow of this study is shown in Table 5.

Table 5. Scripted pipeline components

Script name	Description	Key functions
preprocessing.py	Image preprocessing	Resizing to 512×512, gray world white balance, gamma=2.2
color_conversion.py	Color space conversion	RGB→HSV (Eqs.1-3), RGB→Lab (Eqs.4-6), color moment calculation (Eq.7)
kmeans_clustering.py	K-means clustering	Implementation with k-means++, n_init=10, max_iter=300, random_state=42
cluster_optimization.py	Optimal k selection	Silhouette coefficient (Eq.10) and SSE (Eq.12) calculation
visualization.py	Figure generation	Generates Figs. 5-8 automatically from clustering results
table_generation.py	Table generation	Generates Tables 2-4 from experimental data

4. Discussion

This study innovatively introduced HSV and Lab color spaces into interior design and combined them with K-means and PCCS color coordinate systems. The study linked these color analyses to EN to improve color selection in interior design. Compared with the complex noise-resistant clustering algorithm used by Cai et al. (2024), the K-means algorithm in this study combined dual evaluation of contour coefficients and SSE to improve model interpretability while ensuring clustering stability. In addition, the potential correlation between color composition and emotional attributes could be effectively reflected through the RGB, HSV, and Lab channel distribution of sofa colors in scene 1. This study achieved multi-level fusion from color data to EN, enhancing the relevance and humanization of design decisions. In contrast, Chen et al. (2024) used K-means to process design equipment, while Zhou et al. (2025) considered VR displays for interior design. These two studies did not consider the related design of emotional levels.

This study provided a set of actionable tools to support design managers and project stakeholders. Specifically, managers can use the five EN emotion categories to establish precise, quantifiable color goals with clients in the early stages of the project, thereby avoiding reliance on vague emotional descriptions in communication. In addition, when the design scheme faces customer doubts, designers can refer to the validated perceptual research results in Table 5 to provide evidence-based support for data-driven color selection, thereby reducing subjective debate and the cycle of repeated modifications. In summary, this study can comprehensively consider the color and EN of interior decoration design. At the same time, it provides designers with more intelligent design directions.

5. Conclusion

To efficiently complete interior decoration design, this study used K-means clustering and PCCS to analyze the degree of matching between color selection and EN. Afterward, it defined the color emotion mapping category based on emotional semantics. The results indicated that when K was set to 5, the contour coefficient reached 0.026, and the SSE was approximately 1.5×10^{-8} . At this point, clustering had a better effect. The numerical correspondence among the four scenes across different color spaces confirmed the effectiveness of the color space conversion process, which ensured smooth subsequent EN mapping. The clustering analysis results for different ENs showed that the sample sizes for the modern minimalist ENs, EN2 and EN3, were 367 and 315, respectively. This was consistent with the color description in PCCS. Therefore, the combination of these two factors was reasonable for analyzing color and EN. This study effectively improved the efficiency of decorative design and provided a quantitative basis for color selection in interior design. However, the study did not consider in detail the influence of the material of each interior decoration item on style and EN. In the future, a material perception module can be designed to enhance the technology's comprehensiveness.

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Institutional Review Board Statement

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Declaration of Artificial Intelligence (AI) Tools

The authors confirm that no AI tools were used in the preparation of this manuscript.

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