Research on Color and Texture Characteristics and Visual Perception of Custom Wardrobe Finishes

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In recent years, the custom wardrobe market has been steadily developing. While meeting the functional needs of users, it is gradually shifting towards aesthetic preferences. Rapidly grasping users' preferences for the appearance of custom wardrobes is a key focus of current research. This study collected a large number of decorative surface images of custom wardrobes and objectively analyzed the design features based on color moments and Tamura texture feature data in computer image analysis methods. K-means cluster analysis was performed on the feature data. Collected images of the points closest to the cluster centers were further screened to select representative finish images, and finally a questionnaire survey was conducted at Nanjing Forestry University, with the help of semantic differential method and factor analysis. The characteristics of the samples were comprehensively summarized to infer design elements. The study found that warm-toned, medium-low saturation, and medium brightness surfaces were preferred by the panel. Different colors, contrasts, saturations, brightness, element features, and arrangements have significantly different effects on visual perception. These conclusions can provide a reference for subsequent custom wardrobe design.

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INTRODUCTION

Customized wardrobes show broad prospects for development in the current socio-economic environment due to their high level of personalization and adaptability (Wang *et al*. 2020). In the actual process of wardrobe customization, designers often use style segmentation to explore user preferences and to determine their preferences for the appearance of customized wardrobes. Many users have limited knowledge of styles or may spend a considerable amount of time understanding them, so visual perception is a more accessible way for users to describe their needs. Custom wardrobe finishes boast a rich variety of colors and textures, and different shapes and combinations can evoke different visual perceptions. Therefore, it is significant to explore people's preferences and visual experiences with finishes from the perspectives of color and texture.

The increasing aesthetic demands for furniture appearance have led to surface decoration becoming a focus of research. There are multiple directions emerging in furniture surface decoration. Xiong and Wu (2011) conducted experiments on the simulated crack coating process of rice straw board surfaces after sanding and determined relevant parameters, confirming that the simulated crack coating technology for rice straw boards is suitable for medium-density fiberboard (MDF) furniture. Feng *et al*. (2019)

utilized UV-inkjet 3D printing technology to imitate the texture of wood and printed it onto medium-density fiberboard (MDF). They determined relevant parameters, confirming the feasibility of 3D printing high-performance wood grain coatings on MDF. Wang *et al*. (2021) introduced machine vision technology and unsupervised learning technology. The color moments and color histogram data of beech wood sample images were calculated, and the feature vector set was divided into different clusters for color classification using the K-means algorithm, completing the color classification and texture recognition of beech wood samples. Lungu *et al*. (2022) employed three methods to transfer the two-color patterns from traditional Romanian shirts of Transylvania onto the surface of maple furniture, confirming its applicability for furniture decoration. The study on furniture surface decoration currently focuses more on craftsmanship research rather than the performance aspects.

The color and texture features are important visual characteristics of custom wardrobe finishes. The quantification and description of color and texture features have strong objectivity, enabling in-depth analysis based on feature data to draw more scientific conclusions. Tamura *et al*. (1978) proposed six fundamental texture features based on human visual perception: roughness, contrast, directionality, linearity, regularity, and coarseness, which have contributed to the advancement of image recognition and classification technologies. Zheng *et al*. (2006) compared various image feature extraction techniques, discussing their advantages and disadvantages, as well as their feasibility in different applications. Bianconi *et al*. (2012) developed an expert system for the automatic classification of granite tiles based on computer vision, comparing the performance of different visual features and classifiers across 12 types of granite, demonstrating the feasibility of classification based on color and texture. Chatterjee *et al*. (2015) analyzed the application of computer vision technology in various fields and conducted a comparative analysis of its methods based on the fundamental principles and theories of image processing technology. Qu (2020) analyzed the application of computer vision technology in various fields based on the fundamental principles and theories of image processing techniques through comparative analysis. Kelishadrokhi *et al*. (2023) introduced a method based on the extension of color and texture features known as the Enhanced Local Neighborhood Difference Pattern (ELNDP) for achieving discriminative features, which demonstrated superior retrieval performance. While the extraction and analysis of color and texture features have been applied in multiple fields, there is limited research applying these methods to custom wardrobe finishes.

Visual perception is an important way for humans to perceive the external world. Song and Zhao (2011) explored the visual impression and positioning in the dimensions of perception and emotion of the three cross-sectional profiles of wood, finding differences between softwood and hardwood in the dimensions of perception, emotion, and evaluation, with softwood being more attractive as a decoration. Wang and Zhang (2015) conducted a quantitative study on the sensory characteristics of decorative veneer patterns using the semantic differential method, analyzing their performance in sensory, emotional, and evaluative dimensions, confirming the application value of visual features in the field of design. Litian Sun *et al*. (2018) proposed aesthetic evaluation features based on visual complexity, successfully surpassing photographic rules and deep features through image composition, shape, and distribution attributes, providing an innovative method for photo aesthetic evaluation. Jing Jin and Huaqing Shen (2019) explored the impact of gender, age, cultural differences, and educational level on mobile users' preferences for UI colors on the iPhone 5 through eye-tracking experiments. Thus, several domains have been investigated from a perspective focusing on visual sensation achieving results, but studies related to custom wardrobe finish's visual sensation are still at an initial stage.

Utilizing computer image analysis methods to study underlying image characteristics can explore people's visual sensations towards custom wardrobe finishes. This innovative application enriches academic research within customized wardrobe design field theoretically while indirectly enhancing living environment satisfaction thus promoting industry development.

EXPERIMENTAL

Technical Route

This study focused on the facades of customized wardrobes, exploring their current application and visual perceptibility. The research roadmap, as depicted in Fig. 1, is primarily divided into two parts:

(1) Research on the Current Status of Customized Wardrobe Facade Applications: A substantial collection of facade sample images used for customized wardrobes by upstream supply chain decorative paper companies was gathered. Employing computer image analysis methods (color moments and Tamura texture features), the study extracted color and texture characteristics from all the facade images. An analysis of the feature data was conducted to investigate the current market's facade design and application status.

(2) Research on the Visual Perception of Customized Wardrobe Facade: Initially, the color and texture feature data extracted from the aforementioned research were normalized. Based on this data, K-means clustering analysis was performed. The optimal number of categories was determined using the elbow method, and the facade corresponding to the point closest to the cluster center was identified as the representative facade. Subsequently, through data collection, expert and public discussions, a set of adjective pairs related to visual perception was established for the research samples. A semantic differential method was then used to design relevant questionnaires. Finally, descriptive statistical analysis and factor analysis were conducted on the questionnaire survey data to explore the visual perceptibility preferences for customized wardrobe facades.

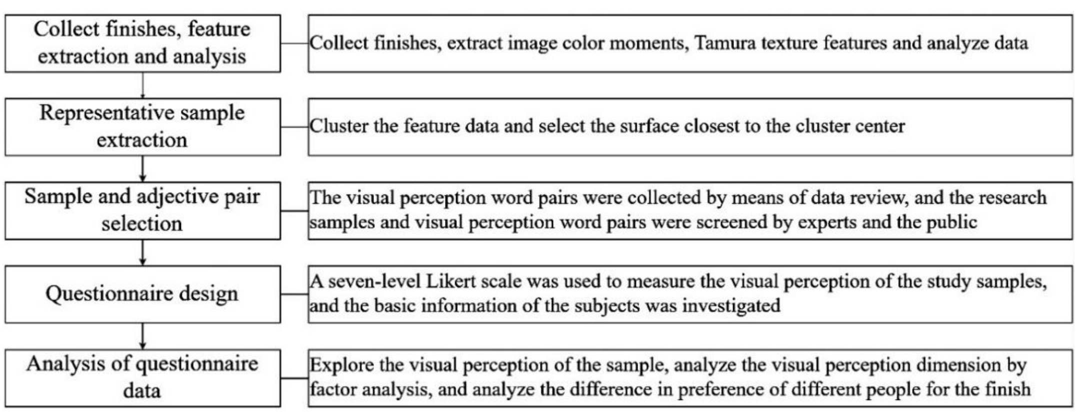


Fig. 1. Basic research approach

Sample Collection

To obtain more accurate market information on current custom wardrobe finishes, this study selected a large number of surface images for analysis. The CNPP Brand List Research Institute data is based on big data statistics and analysis of market and parameter conditions by professionals, presenting the real and objective results of big data, cloud computing, and data statistics. This study takes this list as the foundation. Then there were visits with professors from universities and professionals in the field. After comprehensively considering the completeness of the official website information, eight international decorative paper brands as the data source brands were selected for this study. These brands have stable cooperative relationships with many leading custom home furnishing companies or artificial board enterprises, and their finish designs are representative and forward-looking to a certain extent. The samples were only selected for surface materials used in custom wardrobes, with collection details shown in Table 1.

Table 1. Sample Collection Status

Brand	Number of Finishes	Brand	Number of finishes
Shenglongjinxiu	129	Schattdecor	667
Jiashijia	1003	Interprint	604
Liangshi	259	Lamigraf	611
Zhongrunhuayuan	497	Impress	1734
Total: 5504			

Sample Feature Extraction Method

Color Moment

Current research on color feature extraction from images is relatively mature. Color Coherence Vector, Color Correlogram, Color Histogram, and Color Moment are all main commonly used methods for image color feature extraction. Among the above methods, the most frequently used and relatively easy to operate method is Color Moment, which has the advantages of being easy to implement, describing the global aspects, not being limited by spatial relationships, not being affected by changes in image brightness, and having a wide range of applications. Therefore, this study used Color Moment to extract the color features of custom wardrobe finishes.

The color moment uses the concept of matrix from linear algebra; the color information of the image mainly focuses on low-order moments (Weng *et al*. 2013). The HSV color space is more consistent with human visual system characteristics. Applying research on color features using HSV color space helps improve work efficiency and accuracy. For the color feature extraction method, this study selected color moment extraction based on HSV color space.

The first-order raw moment (mean) describes the average value of color in each color channel of the image; the second-order central moment (variance) describes the dispersion of random variables in the image around the mean, where a larger variance indicates a higher degree of color difference in the image, and a smaller variance indicates better color consistency; the third-order central moment (skewness) describes the degree of asymmetry of the random variables in the image. According to the method of color moment calculation, using the Matlab software for color moment extraction from the surface images, and performing statistical calculations of three orders of moments for the three color channels, a 9-dimensional feature vector is produced. The first-order moments of the H/S/V components represent the average values of the hue, saturation, and value channels, respectively, reflecting the overall tone, saturation, and brightness level of the corresponding surface image; the second-order moments of the H/S/V components represent the standard deviations of the hue, saturation, and value channels, respectively, reflecting the range and degree of variation of the hue, saturation, and brightness of the pixels within the corresponding surface image; the third-order moments of the H/S/V components represent the skewness of the hue, saturation, and value channels, respectively, reflecting the degree of deviation of the distribution of the hue, saturation, and brightness of the pixels within the corresponding surface image. The calculation formulas for the three orders of moments of the color components are as follows:

First-order raw moment (Mean):

$$\mu = \frac{1}{N}\sum_{j=1}^{N} p_{ij} \tag{1}$$

Second-order central moment (Variance):

$$\sigma = \left(\frac{1}{N}\sum_{j=1}^{N} \left(p_{ij} - \mu_i\right)^2\right)^{\frac{1}{2}} \tag{2}$$

Third-order central moment (Skewness):

$$s = \left(\frac{1}{N}\sum_{j=1}^{N} \left(p_{ij} - \mu_i\right)^3\right)^{\frac{1}{3}} \tag{3}$$

where p_{ij} denotes the value of the j-th pixel for the i-th color component, and N represents the total count of pixels.

Tamura texture features

Texture feature extraction and description methods are emerging continuously. As custom wardrobes are products that interact closely with people, the emphasis should be on the human experience and perception of them. Tamura texture features are similar to design studies as they both consider human psychological perception. Tamura *et al.* (1978) proposed six texture features: contrast, roughness, directionality regularity line-likeness coarseness which aligns with human visual perception (Karmakar *et al*. 2017). Therefore, this study used the Tamura texture feature calculation formula and utilized Matlab software to extract texture features from the samples of custom wardrobe finishes. The following are concepts—introduction & calculation—formulas for these six Tamura texture features:

(1) Roughness: Roughness is the most representative intrinsic characteristic of texture features; it reflects the granularity of the image (Pal *et al*. 2018) and can effectively measure the rate of change in the gray level values of the image pixels. The degree of roughness is related to the size and repetition rate of the "basic unit" of the texture; the larger the size of the texture's basic unit and the lower the repetition frequency, the rougher it appears. Conversely, the finer the texture of the image. The calculation process is as follows:

First, calculate the average gray level intensity value of the sample image within a window size of $2k$×$2k$ pixels:

$$A_k(x,y) = \frac{\sum_{i=x-2k-1}^{x+2k-1-1} \sum_{j=y-2k-1}^{y+2k-1-1} f(i,j)}{2^{2k}} \tag{4}$$

The gray level value of pixel (i,j) is denoted by $f(i,j)$.Then, the average intensity difference is calculated between symmetrical, non-overlapping windows in both horizontal and vertical directions for each pixel point, that is:

Horizontal direction:

$$E_{k,h}(x,y) = | \Lambda_k(x+2^{k-1},y) - \Lambda_k(x-2^{k-1},y) \tag{5}$$

Vertical direction:

$$E_{k,v}(x,y) = | \Lambda_k(x,y+2^{k-1}) - \Lambda_k(x,y-2^{k-1}) \tag{6}$$

Subsequently, the optimal neighborhood size is determined, such that it maximizes the E value.

$$S_{\text{best}}(x,y) = 2^k \tag{7}$$

Finally, calculate the average of the best size S_{best} of the sample image and use it as the roughness indicator.

$$F_{\text{crs}} = \frac{1}{m \times n} \sum_{i}^{m} \sum_{j}^{n} S_{\text{best}}(i,j) \tag{8}$$

where m and n correspond to the length and width of the image, respectively.

(2) Contrast: Contrast is used to measure the degree of gray level contrast in an image, which is influenced by the dynamic range of gray levels, the degree of polarization between the black and white parts on the histogram, and the sharpness of edges, and the period of repetitive patterns. The greater the contrast, the stronger the visual impact. The calculation process is as follows:

$$F_{\text{con}} = \frac{\sigma}{\sqrt[4]{\alpha_4}} \tag{9}$$

(3) Directionality: Directionality measures whether an image has a distinct directionality, reflecting the extent to which texture diverges or concentrates along certain directions. The calculation process is as follows:

First, calculate the gradient vector of the pixels in the sample image, including the gradient changes in horizontal and vertical directions:

$$|\Delta G| = \frac{(|\Delta_H| + |\Delta_V|)}{2}, \theta = \tan^{-1}\left(\frac{\Delta_V}{\Delta_H}\right) + \frac{\pi}{2} \tag{10}$$

where ΔH and ΔV are the changes in the gradient vector in the horizontal and vertical directions, respectively.

Then, the distribution histogram HD of θ is constructed,

$$H_D(k) = \frac{N_\theta(k)}{\sum_{i=0}^{n-1} N_\theta(i)} \tag{11}$$

where n represents the quantization level of the directional angle, $N\theta(k)$ is the number of pixels when ΔG is greater than the threshold, and $(2k-1)\pi/2n \leq \theta \leq (2k+1)\pi/2n$. When the image has a distinct directionality, the histogram HD exhibits peaks; otherwise, the distribution is uniform. The formula for calculating the directionality is:

$$F_{\text{dir}} = \sum_{p}^{n_p} \sum_{\varphi \in w_p} \left(\varphi - \varphi_p\right)^2 \cdot H_D(\varphi) \tag{12}$$

where n_p is the number of peaks in the histogram, p represents the peak of the histogram,

w_p is the range of quantized values that the peak encompasses, and ϕ_p is the quantized value within the maximum histogram value.

(4) Linearity: Linearity is used to measure whether the "basic units" of the texture within the image are arranged in a linear or strip-like pattern.

$$F_{\text{lin}} = \frac{\sum_i^n \sum_j^n P_{Dd}(i,j)\cos\left[(i-j)\frac{2\pi}{n}\right]}{\sum_i^n \sum_j^n P_{Dd}(i,j)} \tag{13}$$

where P_{Dd} represents the distance points of the $n\times n$ local directional co-occurrence matrix.

(5) Regularity: Regularity characterizes whether the texture exhibits a distinct regularity.

$$F_{\text{reg}} = 1 - r(\sigma_{\text{crs}} + \sigma_{\text{con}} + \sigma_{\text{dir}} + \sigma_{\text{lin}}) \tag{14}$$

(6) Coarseness: Coarseness simulates to a certain extent the roughness perceived by the sense of touch.

$$F_{\text{rgh}} = F_{\text{crs}} + F_{\text{con}} \tag{15}$$

Questionnaire Design

To explore the visual preferences of different users for customized wardrobe surface finishes, this study conducted a survey through online questionnaire distribution. The first part of the questionnaire surveyed basic user information, including gender, age, education, and other basic details. The second part consisted of a seven-point Likert scale visual perception test for the sample surfaces, where respondents were required to rate different perceptual dimensions of various surfaces. The lower the score, the more inclined the respondent was towards the adjective on the left; the higher the score, the more inclined towards the adjective on the right. A score of “0” indicates neutrality with no clear inclination. To prevent a decline in response quality due to visual and mental fatigue during the questionnaire test, it is necessary to streamline the number of test samples and pairs of perceptual adjectives. The following is the process for selecting test samples and adjective pairs in this study:

The selection process for test samples is shown in Fig. 2. The color and texture of customized wardrobe surface finishes are important visual characteristics that greatly influence the visual perception of the surfaces. This study initially extracted the underlying features of the surface images from the perspectives of color and texture. The feature data were normalized and subjected to K-means clustering. By plotting the relationship between the sum of squared errors (SSE) corresponding to different K values and the K values, as shown in Fig. 3. An “elbow” will appear in the line graph; after this point, continuing to increase the K value will cause the slope of the curve to change abruptly, meaning the rate of decrease in the sum of squared errors will decrease sharply. By using the elbow method, the optimal number of clusters was determined to be 56. Then, the surface images corresponding to the points closest to the cluster centers were identified. Finally, 16 test samples used for the study were further selected based on expert and public discussion and evaluation, as shown in Fig. 4.

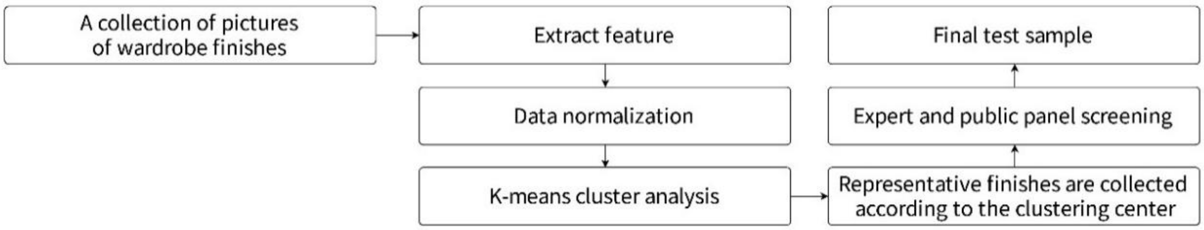


Fig. 2. Sample screening process

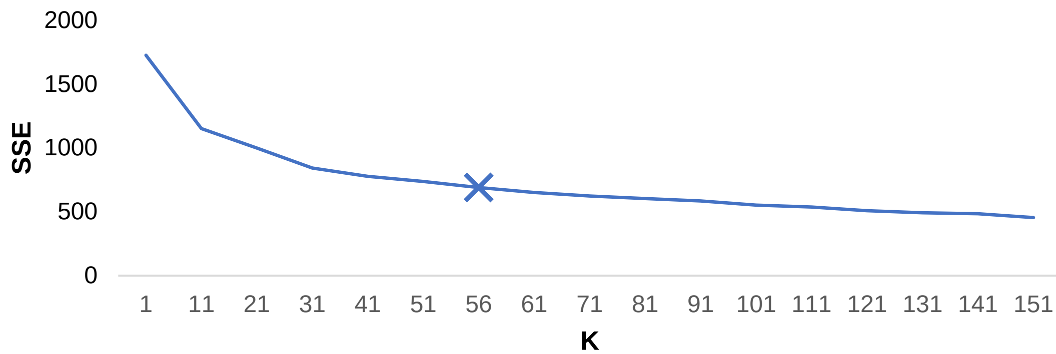


Fig. 3. The line chart that corresponds the sum of squared errors (SSE) to different values of K

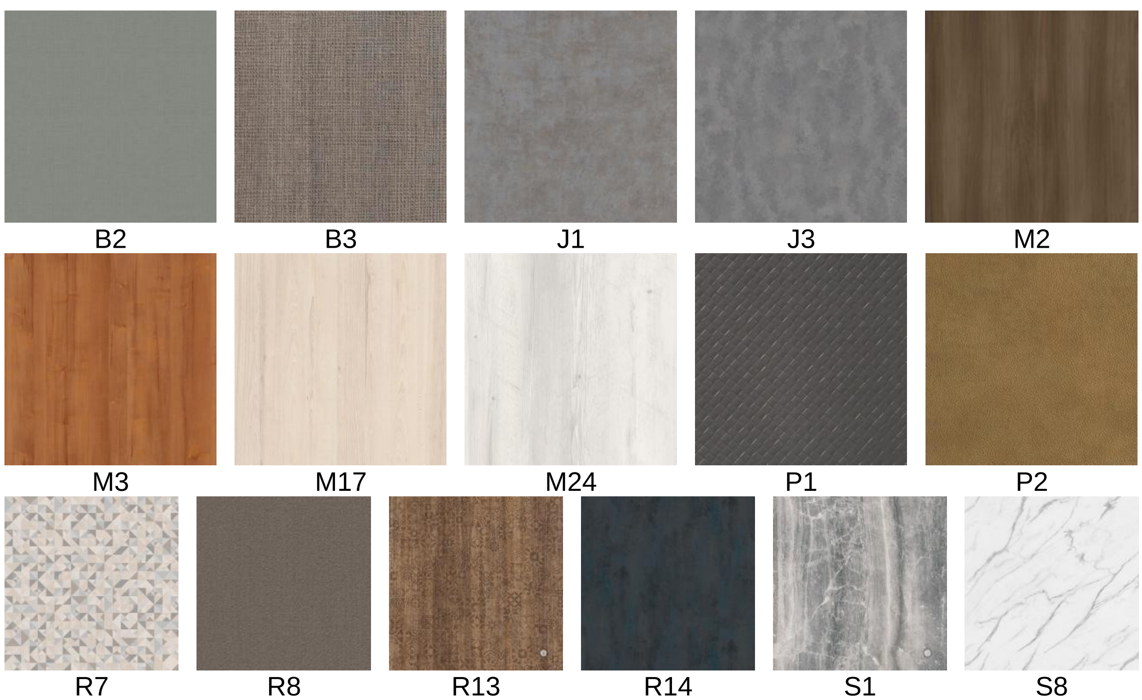


Fig. 4. Sample set of finishes for testing

In the scale test items, it is necessary to define the perceptual dimensions of the users. This study conducted a collection of vocabulary through extensive literature, books, and other materials related to "design" and "visual perception," organizing adjectives through brainstorming to obtain 140 pairs of adjectives related to both. Subsequently, through discussions with six professionals related to home design and four general consumers, synonyms in the adjective collection were organized and those unsuitable for describing the visual perception of custom wardrobe finishes materials were eliminated. The final semantic vocabulary collection selected 8 pairs of adjectives, which are: rough and smooth, traditional and modern, complex and simple, indifferent and warm, natural and artificial, static and dynamic, soft and rigid, abstract and concrete. The final semantic scale test items are shown in Table 2.

Table 2. Semantic Variance Header Example

Sample question	Score/degree	-3	-2	-1	0	1	2	3	
	rough	○	○	○	○	○	○	○	smooth
	traditional	○	○	○	○	○	○	○	modern
	complex	○	○	○	○	○	○	○	simple
	cold	○	○	○	○	○	○	○	warm
	natural	○	○	○	○	○	○	○	artificial
	static	○	○	○	○	○	○	○	dynamic
Sample number: R14	gentle	○	○	○	○	○	○	○	hard
	abstract	○	○	○	○	○	○	○	concrete

RESULTS AND DISCUSSION

Matlab was utilized to extract color moment and Tamura texture features from the collected surface images. The color moment data reflect the average values and standard deviations of the hue, saturation, and brightness components of each surface image. The mean represents the average hue, saturation, and brightness information of each pixel in the image after individual calculations. The standard deviation indicates the extent of variation in hue, saturation, and brightness within each surface image. The Tamura texture features calculated the contrast, directionality, roughness, regularity, linearity, and coarseness for each surface. Through the analysis of color moments and Tamura texture features, the distribution characteristics of the color and texture information of the surfaces can be summarized. Cluster analysis of the color and texture feature data can be used to select representative surfaces for visual perception research. The visual perception of each surface can be measured using the semantic differential method. Factor analysis can further delineate the dimensions of perception, and inductive reasoning can summarize the design elements corresponding to each visual perception.

Customize Wardrobe Finishes with Color and Texture Features

Overall analysis of hue

The range of hues is 0 to 360° including six basic colors: red, yellow, green, cyan, blue, and magenta. An additional 6 intermediate hues are inserted between adjacent primary hues resulting in a total description with 12 hues as shown in Fig. 5.

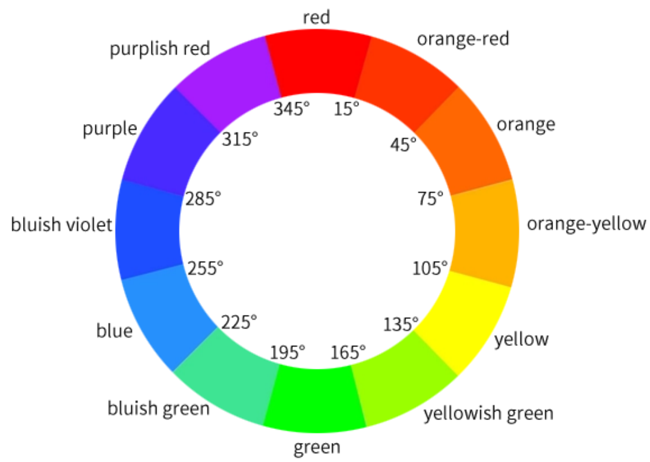


Fig. 5. Hue degree and color correspondence

An analysis was conducted on the average hue of the collected surface images. The distribution of the average hue is depicted in Fig. 6, in which custom wardrobe finishes in the orange color family account for 75% of the total. Surface finishes with an orange hue, predominantly wood grain, are the most widely used. Orange is a bright and warm hue that can provide a visually warm and pleasant experience when applied to interior spaces. After excluding the orange color family, the statistics still show that warm color family finishes represented by the yellow hue are the most prevalent. In addition, it is possible that people have a greater preference for finishes in the blue color family. The blue hue is typically associated with feelings of calmness and relaxation. When applied to custom wardrobe, with different levels of saturation and brightness, it can offer a refreshing or profound visual experience. As people's aesthetic preferences become more diverse, there is also significant room for development in the blue color family of custom wardrobe finishes.

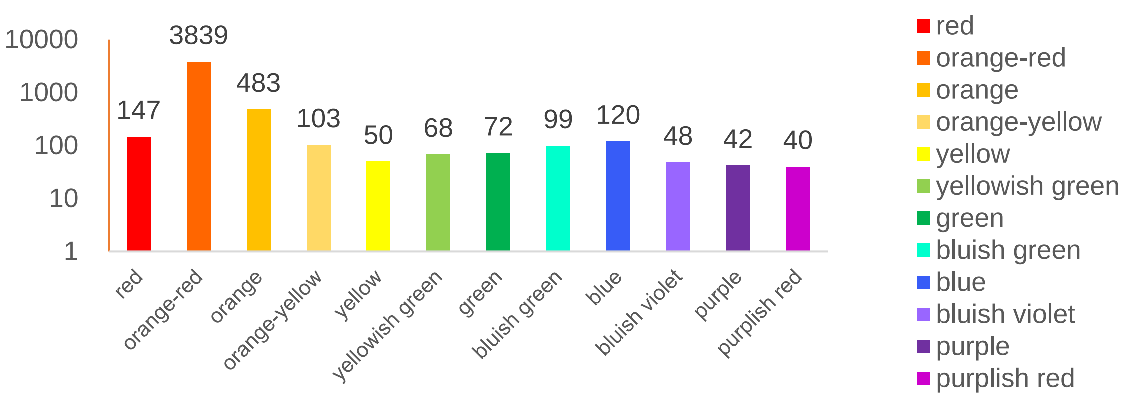


Fig. 6. Statistical distribution of average hue of each finish picture

Saturation overall analysis

Saturation (S) represents the purity of a color, indicating the proportion of gray components within the color. The effective value range is 0 to 100%. The levels of saturation are categorized as shown in Fig. 7.

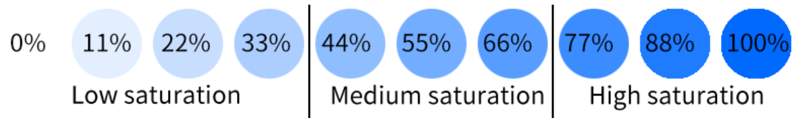


Fig. 7. Saturation grade classification basis

Upon organizing and analyzing the average saturation of the collected surface images, the distribution of saturation is depicted in Fig. 8. Seventy-three percent of the surfaces were of low saturation, which suggests that in custom wardrobe products, people predominantly use surfaces with low saturation. Low saturation surfaces are less likely to cause visual fatigue even when viewed for extended periods, providing a comfortable and relaxing sensation. Surfaces with medium saturation account for 25% and also have a considerable application and audience base. High saturation surfaces only make up 2%, with a total of 113 images. Surfaces with high saturation typically have a strong visual impact and can lead to adverse visual experiences when used in environments where people live or work for long periods. Additionally, due to their prominent colors, they are less compatible with other elements. As a result, high saturation surfaces are less frequently used in custom wardrobes. Observing the distribution of surfaces after dividing saturation into nine levels, it is evident that the number of surfaces with the lowest level of saturation is the highest. As the saturation increases, the number of surface images decreases sharply, indicating a clear preference for low saturation surfaces in custom wardrobe, with very little demand for high saturation surfaces.

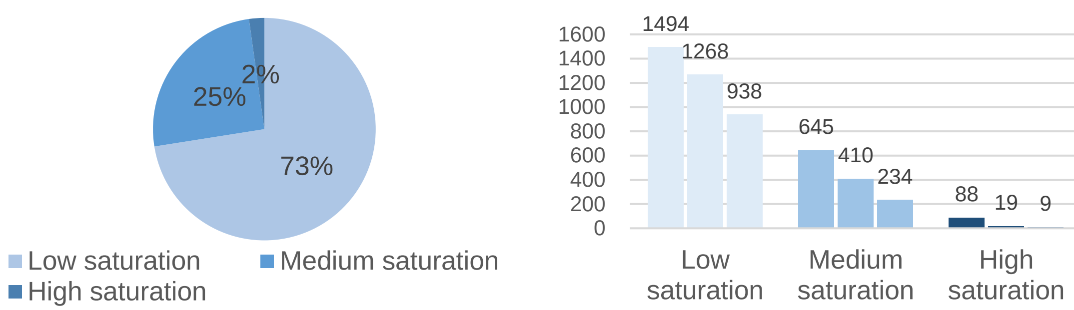


Fig. 8. Statistical distribution of average saturation of each face image

Brightness overall analysis

Brightness (V) indicates the lightness or darkness of a color, with an effective value range identical to that of saturation, that is, 0 to 100%. At 100%, the brightness is the highest, approaching white; at 0%, the brightness is the lowest, approaching black. The levels of brightness are categorized as shown in Fig. 9.

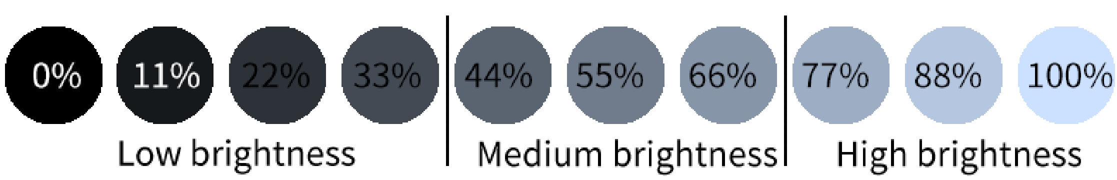


Fig. 9. Brightness level classification basis

Upon organizing and analyzing the average hue of the collected surface images, the distribution of brightness is depicted in Fig. 10. Surfaces with high brightness constitute the main portion, approximately 43%. Surfaces with high brightness are widely used in custom wardrobe due to their strong reflective capabilities, making them particularly suitable for small-sized homes and interior spaces with poor lighting. Surfaces with medium brightness make up 39% of the main body, only 4% less than those with high brightness. Medium brightness surfaces are also relatively widely used, with the advantage of having a strong ability to brighten the space and being more visually comfortable for the human visual system, not easily causing visual fatigue over long periods of observation, and providing a comfortable and warm visual experience. Surfaces with low brightness are used the least but still account for 18% of the main body. Applying low brightness surfaces in custom wardrobe may make the space seem cramped and oppressive, lacking a sense of transparency. Observing the distribution of surfaces after dividing brightness into nine levels, it can be found that the application of custom wardrobe finishes does not steadily increase with the enhancement of brightness. Instead, there is a downward trend after a certain level of brightness, indicating that people's preferences for surfaces do not have a completely positive correlation with the brightness of the surfaces. Surfaces with "moderately high" and "high but slightly low" brightness values are the most preferred for use in custom wardrobe.

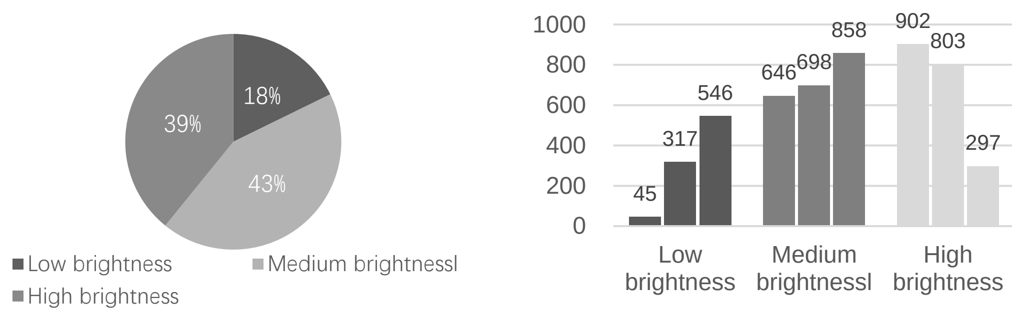


Fig. 10. Statistical distribution of average brightness of each finish picture

Color variation analysis

A single surface image contains multiple pixel points, and pixel points within the same surface image may have different color characteristics. The second-order moment data of the color moment is the standard deviation of the hue, saturation, and brightness values of each surface image, reflecting the extent of variation in color across the three dimensions of hue, saturation, and brightness. The mean values of the standard deviations for hue, saturation, and brightness of each category of surface are plotted in a line chart for comparison, as shown in Fig. 11. From the perspective of hue, the variation in color hue is greatest in stone surfaces, and smallest in fabric textures, meaning that stone surfaces have the largest hue contrast, while fabric textures have the most uniform hue. From the perspective of saturation, the variation in color saturation among all surfaces is relatively small, with fabric textures showing the least variation in color saturation. From the perspective of brightness, the variation in color brightness is greatest in stone-patterned surfaces, and smallest in wood grain surfaces. Overall, the variation in color hue is the greatest for all types of customized wardrobe surfaces, indicating that the variation and difference in color hue within a customized wardrobe surface are the most significant. The overall variation and difference in color saturation are relatively small. Stone-patterned surfaces have the largest color variation, while fabric and wood grain surfaces have the smallest color variation differences.

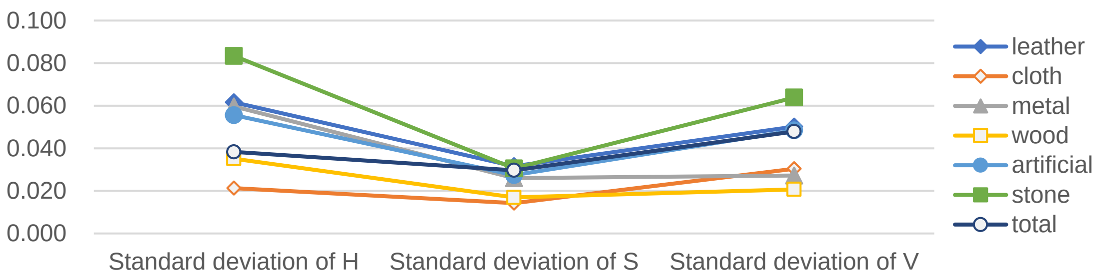


Fig. 11. Comparison of mean values of H/S/V standard deviation for each type of finish

Texture feature data analysis

The Tamura texture features of all collected surfaces were calculated and the results were classified and analyzed. The mean values of six feature items for fabric texture, leather texture, metal texture, wood texture, artificial pattern texture, and stone texture were calculated and are shown in Table 3. An exploration of the texture characteristics of each type of surface was conducted, followed by a comprehensive comparative analysis.

Table 3. Average Tamura Texture Features for Each Type of Finish

Type	Contrast	Directionality	Coarseness	Line-likeness	Regularity	Roughness
Cloth	93.16762950	27.15547707	12.1519265	0.16504986	0.977880473	105.319556
Leather	136.4728422	29.68317743	13.04735172	0.059580924	0.981604304	149.5201939
Metal	48.56631315	35.52359262	15.10930072	0.06339587	0.970129904	63.67561387
Wood	134.0654041	10.69558503	15.29204679	0.354031064	0.988372203	149.3574509
Artificial	220.0828589	28.25202977	14.25489865	0.175903181	0.97197105	234.6024333
Stone	259.5847578	32.93374684	15.75653493	0.045304797	0.965998656	275.3412927

In the comparative analysis of the mean values of the six major features across various types, stone textures generally exhibit a higher contrast, with most stone textures used in custom wardrobe finishes featuring a greater degree of grayscale contrast. The average directionality of wood textures is the lowest, a result of the natural growth characteristics of wood grain, but this is also one of the reasons why wood grain is favored by people. The mean roughness values of various types of surfaces show little variation, indicating that the fineness of the patterns across different types of surfaces does not fluctuate greatly and are generally quite delicate in texture. Wood grain has the most pronounced average linearity and regularity, suggesting that the basic units of wood grain texture are mostly linear and the arrangement is also generally consistent. The average coarseness of stone textures is the highest, indicating that the visual tactile roughness of stone surfaces in custom wardrobe is the greatest, while that of metal textures is the lowest.

Custom Wardrobe Finish Visual Feel and Design Elements

Using a targeted sampling approach, an online questionnaire was distributed and surveyed, and a total of 120 questionnaires were collected. After verification, 4 invalid questionnaires were discarded, leaving 116 valid questionnaires. The survey subjects for this study were faculty and students from Nanjing Forestry University and employees of a certain custom furniture company, with the basic situation shown in Fig. 12. Using the SPSS software to perform reliability and validity analysis on the questionnaire data, it can be seen that the Cronbach's alpha coefficient (α coefficient) of the results of this questionnaire was 0.936, which indicates that the results of this experimental questionnaire had a high degree of reliability. The KMO value was 0.679 > 0.6, and the significance p-value was 0.001 < 0.005. That is, the KMO value > 0.6 and the p-value of the Bartlett test < 0.005, indicating that the data had correlation and is suitable for factor analysis in subsequent research. The average evaluation scores for each sample and the comprehensive evaluation score for all samples, which is the average score for each sample, were derived. The visual perception evaluation curves for each sample and the comprehensive evaluation curve for all samples are plotted as shown in Fig. 13. The average scores for each surface sample were all greater than 0, indicating that the visual perception of the sample surfaces tends to be smooth, modern, simple, warm, artificial, dynamic, and concrete. All sample scores fell within the range of -1 to 1.5, suggesting that the overall visual perception of custom wardrobe finishes varied within a stable range. Among them, surface B3 had a significantly rougher visual perception compared to other surfaces, surface R7 has a significantly more dynamic visual perception, and surface R13 had a significantly more complex element composition. In the comparison of evaluation scores, there was a larger difference in scores in the dimensions of V1, V3, V4, and V5, indicating that there was a greater difference in visual perception among the samples in these aspects. The distribution was more concentrated in the dimensions of V7 and V8, indicating that the differences in visual perception among the surface samples in these two dimensions were smaller.

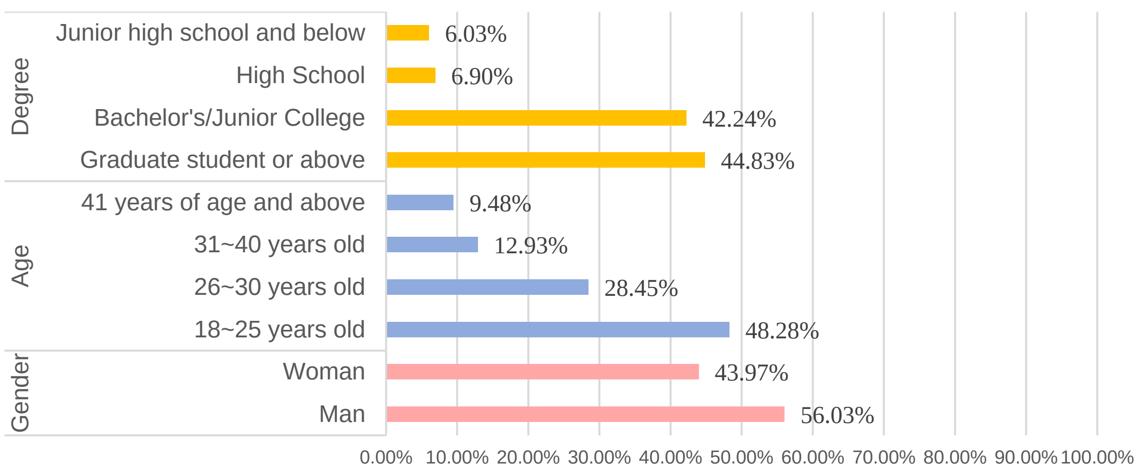


Fig. 12. Survey subjects' basic information statistics

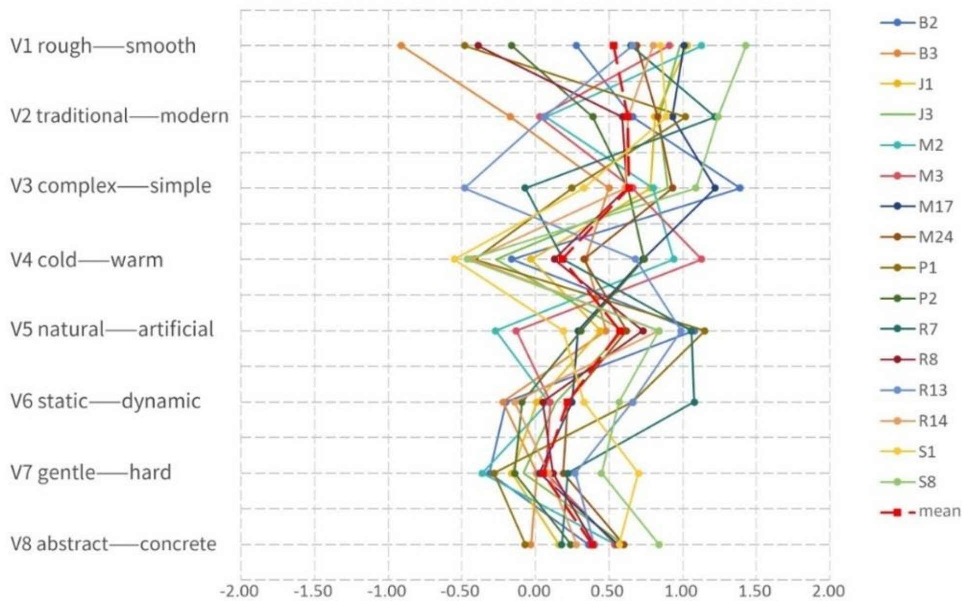


Fig. 13. Comprehensive evaluation curve of the test sample

The dataset was subjected to direct orthogonal rotation using the Maximum Variance Rotation method, followed by the extraction of factors with an eigenvalue greater than 1, which serve as the primary factors for the design characteristics of custom wardrobe finishes. As shown in Table 4, there were three factors with eigenvalues greater than 1, which were 2.628, 2.272, and 1.543, respectively. The variance explanation rates after rotation for these three factors were 28.807%, 27.807%, and 23.933%, respectively. The cumulative variance explanation rate after rotation was 80.547%. Therefore, a total of three primary factors were selected from the data, and these three factors represent the most significant design characteristic factors for custom wardrobe finishes.

Table 4. Table of Explained Rates of Variance

Factor	Initial eigenvalue			Extract the sum of squared loads			Rotating load sum of squares		
	Total	Variance (%)	Accum-ulation	Total	Variance (%)	Accum-ulation	Total	Variance (%)	Accumu-lation
1	2.628	32.855	32.855	2.628	32.855	32.855	2.305	28.807	28.807
2	2.272	28.399	61.254	2.272	28.399	61.254	2.225	27.807	56.614
3	1.543	19.294	80.547	1.543	19.294	80.547	1.915	23.933	80.547
4	0.738	9.223	89.771						
5	0.347	4.342	94.113						
6	0.312	3.901	98.014						
7	0.117	1.462	99.476						
8	0.042	0.524	100						

The component matrix after factor rotation is shown in Table 5. Looking at the factor loadings, in Factor 1, the pair of adjectives “soft-hard” and “indifferent-warm” have large absolute values of loadings, and both are descriptions of the psychological feelings that the surface brings to people, hence it is named the “Psychological Perception Factor.” In Factor 2, the pairs “rough-smooth,” “traditional-modern,” and “natural-artificial” have large absolute values of loadings, and all are factors describing the overall presentation of the surface, thus it is named the “Overall Presentation Factor.” In Factor 3, the pairs “complex-simple,” “static-dynamic,” and “abstract-concrete” have large absolute values of loadings, and all are descriptions of the composition of the surface elements, therefore it is named the "Element Composition Factor."

Table 5. Visual Receptor Factor Load Scale

	Factor 1	Factor 2	Factor 3
rough-smooth	0.016	-0.886	0.062
traditional-modern	0.319	0.857	0.117
complex-simple	0.386	0.168	-0.870
cold-warm	0.881	0.03	0.200
natural-artificial	-0.402	0.746	0.271
static-dynamic	0.474	0.3	0.61
gentle-hard	0.933	0.169	-0.049
abstract-concrete	0.14	-0.041	0.832

In response to the visual perception of surfaces, the extreme value samples corresponding to each set of adjectives were identified, which facilitated the analysis of the elements that lead to changes in visual perception. The color and texture characteristic values of each extreme value representative sample are shown in Tables 6 and 7.

By observing the three main factors of visual perception and the corresponding reference surfaces, and by combining the characteristics of each sample in terms of color, elements, and composition methods, a comprehensive analysis was conducted to summarize the commonalities. This process led to the induction and summary of the forms of expression of design elements corresponding to different main factors of visual perception. In the Overall Presentation Factor, the representative samples were B3, P2, and S8. All three stood out in "Overall Presentation" through the expression of different design elements and are thus studied as representative samples for design element research. B3 gives a more pronounced feeling of being rough, traditional, and artificial; P2 gives a rough and natural feeling; S8 gives a smooth, modern feeling. In a comprehensive comparison, it was found that surfaces with higher contrast, low saturation, medium brightness, and closely arranged composition elements are more likely to give a rough feeling; surfaces with single elements, simple and irregular composition, and high brightness are more likely to give a smooth, modern feeling; surfaces with dull colors, varied element shapes, and higher contrast are more likely to give a traditional feeling.

Table 6. Color and Texture Characteristic Values of Representative Samples

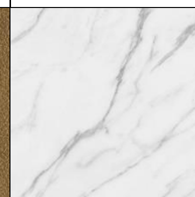
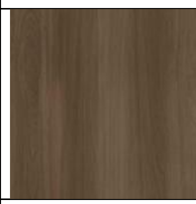
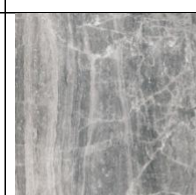
Principal Factor	Overall Performance			Element Composition	
Visual perception	rough traditional artificial	rough natural	smooth modern	simple static	complex dynamic abstract
Sample part					
Average hue value	29.06°	35.02°	0°	85.71°	30.23°
Average saturation	13.9%	9.7%	0%	5.1%	52.5%
Average brightness	49.7%	51.6%	90.8%	53.6%	42.0%
Contrast	801.394	362.847	39.432	12.503	306.027
Directivity	18.589	16.317	12.995	44.334	20.195
Coarseness	11.410	10.517	20.232	11.676	20.340
Line-likeness	0.041	0.047	0.083	0.049	0.139
Regularity	0.991	0.990	0.962	0.971	0.996
Roughness	812.804	373.364	59.665	24.178	326.368

Table 7. Color and Texture Characteristic Values of Representative Samples

Principal Factor	Element Composition	Psychological Feeling		
Visual perception	Complex concrete	warm gentle	warm	hard cold
Sample part				
Average hue value	25.69°	31.29°	24.06°	148.52°
Average saturation	38.8%	38.8%	64.4%	3.0%
Average brightness	33.6%	38.7%	64.3%	65.6%
Contrast	6.410	36.321	39.644	490.902
Directivity	2.141	2.481	4.991	15.367
Coarseness	12.934	21.975	21.345	18.605
Line-likeness	0.237	0.281	0.272	0.079
Regularity	0.958	0.991	0.985	0.955
Roughness	19.345	58.297	60.989	509.507

In the Element Composition Factor, the representative samples are B2, R7, and R13. All three stood out in “Element Composition” through the expression of different design elements. Compared to other textured surfaces, those designed by humans had a richer variety of elements. B2 gives a simple, static feeling; R7 gives a complex, dynamic, and abstract feeling; R13 gives a complex and concrete feeling. Upon comprehensive comparison, it is found that extremely fine textures, cool tones, and low saturation are more likely to give a static feeling; surfaces with single elements, single colors, and simple element arrangement are more likely to give a simple feeling; surfaces with a combination of elements of different shapes, colors, and sizes, and medium saturation and brightness are more likely to give a complex and concrete feeling; surfaces with geometric shapes, approximate composition, and varying colors are more likely to give a dynamic and abstract feeling.

In the Psychological Perception Factor, the representative samples are M2, M3, and S1. All three stood out in "Psychological Perception" through the expression of different design elements. Both M2 and M3 gave a warm feeling, with M2 being softer, while S1 gave a hard and indifferent feeling. Surfaces with wood grain or imitation wood grain elements, warm color adjacent color matching, and slightly curved curve textures are more likely to give a warm feeling; surfaces with lower saturation and brightness, lower contrast, and slightly curved curve textures are more likely to give a soft feeling; surfaces with cool color tones, low saturation, high brightness, and high contrast stone textures are more likely to give a hard and indifferent feeling.

CONCLUSIONS

1. Through the analysis of color feature data, it was found that surfaces with orange and yellow hues account for about 85% of the total, being more favored by the market and users; surfaces with high saturation only account for 2%, indicating that user visual preference for surfaces decreases with increasing saturation. The most preferred levels of surface brightness are "moderately high" and "slightly low"; in custom wardrobe surfaces, the degree of hue change is greater than the brightness change, which is greater than the saturation change, with stone texture surfaces showing the greatest degree of color change and fabric textures the least, indicating that stone texture surfaces are mostly used for contrasting color combinations. Through the analysis of texture feature data, it was found that the texture of custom wardrobe surfaces generally has a high degree of fineness, and people generally prefer a fine texture for wardrobe surfaces. Among the mean values of the six major features of each type, stone textures generally have a larger contrast, and wood textures have a strong natural attribute. The natural growth of wood grain results in the randomness of texture direction, hence having the lowest average directionality and the most pronounced average linearity and regularity. Based on the visual preferences of users for finishes and the characteristics of various types of finishes, related companies can develop products that better meet market demands.
2. The visual perception of custom wardrobe surfaces can be divided into three levels: the psychological perception level, the overall presentation level, and the element composition level. The psychological perception level includes two dimensions: "soft-hard" and "indifferent-warm"; the overall presentation level includes three dimensions: "rough-smooth," "traditional-modern," and "natural-artificial"; the element composition level includes three dimensions: "complex-simple," "static-dynamic," and "abstract-concrete." This can more specifically help us understand the visual characteristics of custom wardrobe finishes.
3. Analyzing from the three levels of visual perception, corresponding design elements are derived from the analysis of prominent reference surface samples. It was found that surfaces with higher contrast, low saturation, medium brightness, and closely arranged composition elements are more likely to give a rough, traditional, and artificial visual

perception. Surfaces with single elements, simple and irregular composition, and high brightness are more likely to give a smooth, modern feeling. Surfaces with a combination of elements of different shapes, colors, and sizes, and medium saturation and brightness are more likely to give a complex and concrete feeling; surfaces with geometric shapes, approximate composition, and varying colors are more likely to give a dynamic and abstract feeling. Surfaces with warm color adjacent color matching, lower contrast, and slightly curved curve textures are more likely to give a soft and warm feeling; surfaces with cool color tones, low saturation, high brightness, and high contrast stone textures are more likely to give a hard and indifferent feeling. This study explored the visual perception of custom wardrobe finishes from a holistic perspective, providing a reference for the subsequent design of custom wardrobe finishes. Future research can further focus on specific design elements for targeted visual perception studies.

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