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A Structured Translation and Evaluation of Dunhuang Mural Color and Patterns in Modern Silk Scarf and Evening Dress Design

Xiaochen Shen

Academy of Fine Arts, Xinxiang University, Xinxiang 453000, Henan, China
damaomao1026@163.com

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ABSTRACT

Dunhuang mural art provides rich visual resources for contemporary textile and apparel design, yet its application in modern products often depends on intuitive borrowing rather than structured translation. To address this issue, this study proposes a quantitative framework for translating and evaluating Dunhuang mural color and pattern features in silk scarf and evening dress design. Representative mural images were first processed using digital image analysis to extract dominant color composition, perceptual color contrast, pattern density, and orientation characteristics. These features were then aggregated into three representative visual prototypes, from which six design schemes were generated through a rule-guided translation strategy. To evaluate the design outcomes, a multi-criteria framework combining the Analytic Hierarchy Process and fuzzy comprehensive evaluation was employed. The results indicate that schemes with stronger cultural feature retention achieved higher scores in cultural expression but lower scores in practicality and perceived market acceptance because of increased visual complexity. In contrast, more balanced schemes obtained better overall performance. The proposed framework improves the reproducibility and evaluability of culturally inspired design and provides methodological support for integrating traditional visual heritage into modern textile and apparel products.

KEYWORDS
dunhuang mural, textile design, color feature extraction, pattern analysis, AHP-fuzzy evaluation

INTRODUCTION

Traditional cultural heritage provides rich visual resources for contemporary design innovation, particularly in textile and apparel design. Among various design factors, color plays a central role in shaping visual perception, emotional response, and aesthetic judgment. Previous studies have shown that color combinations can evoke different emotional reactions across media contexts [1]. In addition, individual color preferences have been found to influence consumer purchase decisions, indicating that color is not only a visual element but also an important factor affecting product acceptance in design practice [2]. Recent studies have further emphasized that traditional cultural colors can be revitalized through structured emotional and digital customization approaches, providing useful support for transforming cultural color systems into contemporary design resources [3]. Therefore, the study of cultural color systems is of considerable significance for both aesthetic expression and market-oriented design.

In recent years, the integration of traditional cultural elements into modern fashion products has attracted increasing attention. Studies on Dunhuang-inspired clothing design have shown that traditional cultural narratives and symbolic elements can be effectively reinterpreted in contemporary apparel, thereby enhancing cultural identity and design expression [4]. However, many existing design practices still rely heavily on subjective inspiration, direct borrowing, or decorative imitation, and lack a systematic method for translating traditional visual resources into modern design language. This limitation is particularly evident in the application of culturally rich visual systems, in which both color organization and pattern structure are highly complex. As a result, the final design outcomes often exhibit insufficient consistency, limited reproducibility, and weak methodological transparency.

With the development of digital technology, image processing methods provide a more structured and reproducible basis for analyzing and extracting visual features from cultural images. Digital image processing has been widely applied to image enhancement, segmentation, feature extraction, and pattern recognition, offering a solid technical foundation for the structured analysis of visual materials [5,6]. Among these methods, edge detection is an effective tool for identifying contour information and structural boundaries in images. The classical Canny operator is particularly suitable for extracting detailed edge features with relatively strong noise resistance [7]. In addition, texture analysis methods based on statistical descriptors can capture the spatial distribution and structural characteristics of image patterns, which are useful for describing the organization of decorative motifs [8].

For color analysis, clustering-based methods provide a practical way to transform complex color information into quantifiable variables. K-means clustering has been widely used to group similar pixels and extract dominant color components from images because of its simplicity and effectiveness [9]. Meanwhile, the CIEDE2000 color-difference formula has been widely adopted in color science and image analysis to evaluate color differences in a perceptually meaningful manner [10]. By combining clustering and perceptual color-difference measurement, it becomes possible to characterize traditional color systems in a structured and computable form.

Although digital image analysis provides useful technical support, the translation of extracted cultural features into modern textile and apparel design still requires a rational evaluation framework. In this regard, multi-criteria decision-making methods offer an effective solution. The Analytic Hierarchy Process (AHP) enables the hierarchical decomposition of complex design problems and the determination of criterion weights through pairwise comparison [11]. At the same time, fuzzy set theory provides a means of describing ambiguity and uncertainty in subjective evaluation [12]. Based on these principles, fuzzy multiple-attribute decision-making methods can be used to synthesize expert judgments and generate comprehensive evaluation results for design schemes [13]. In the present study, expert participation was introduced as an interpretive refinement mechanism to improve visual coherence and design readability, rather than to replace quantitative feature analysis.

Based on the above considerations, this study proposes a structured framework for translating cultural visual elements into modern silk scarf and evening dress design. The framework combines digital image processing for feature extraction, clustering and color-difference analysis for quantitative representation, and an AHP–fuzzy evaluation model for design assessment. Through this approach, the study aims to improve the consistency, reproducibility, and evaluability of culturally inspired design, and to provide a methodological reference for the innovative application of traditional visual resources in modern textile and apparel products.

MATERIALS AND METHODS

Data Sources and Image Preprocessing

Representative Dunhuang mural images were used as the original visual source for feature extraction. A total of 15 images were selected from publicly accessible digital archives and published visual materials. To reduce excessive heterogeneity, the selected samples were limited to mural fragments with relatively clear color composition and identifiable decorative motifs. The inclusion criteria were as follows: (1) distinguishable color regions suitable for clustering analysis; (2) relatively intact pattern structures; and (3) sufficient image resolution for digital processing. Images with severe fading, large missing regions, or highly fragmented motifs were excluded.

The overall framework of the proposed method is illustrated in Figure 1.

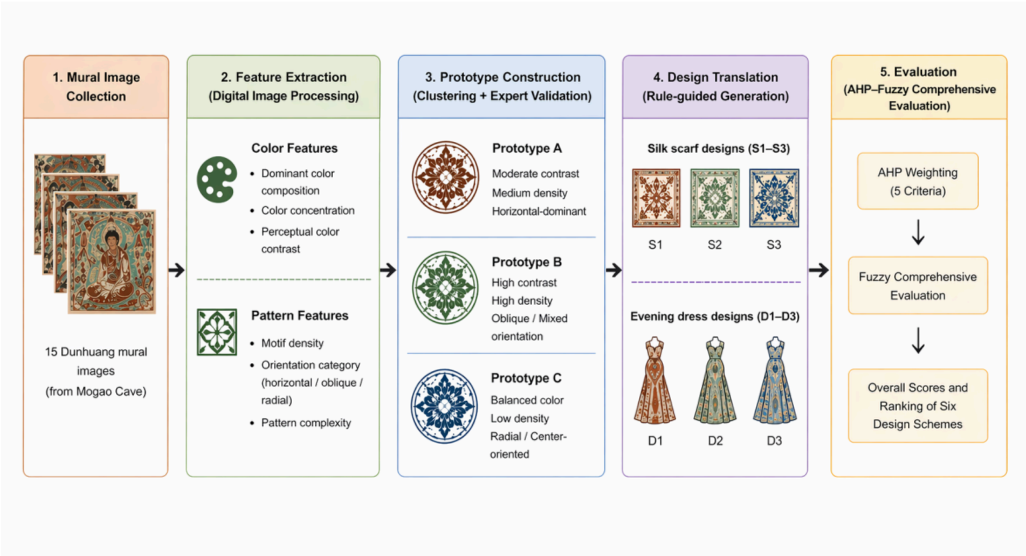

Figure 1. Framework of the proposed method for Dunhuang mural feature extraction, prototype construction, design translation, and multi-criteria evaluation

To ensure comparability, all images were standardized to a resolution of 512 × 512 pixels before analysis. Basic preprocessing operations, including contrast adjustment and pixel normalization, were performed according to standard digital image processing procedures [5]. For color analysis, all images were converted from RGB space to CIELAB (L*a*b*) space, as this color space is more appropriate for perceptual color comparison [10].

Feature Extraction of Color and Patterns

Color features were extracted using K-means clustering [9]. Before determining the final parameter setting, preliminary tests were conducted with $k = 4, 5, 6, 7$, and 8 . When $k \leq 5$, some visually distinct secondary colors were frequently merged into dominant clusters, resulting in oversimplified color representation. By contrast, when $k \geq 7$, redundant minor clusters repeatedly appeared, reducing interpretability for subsequent design translation. Therefore, $k = 6$ was adopted as a compromise between descriptive adequacy and practical interpretability.

The clustering objective is defined as:

$$J = \sum_{i=1}^{k} \sum_{x \in C_i} \parallel x - \mu_i \parallel^2 \tag{1}$$

where C_i denotes the set of pixels assigned to cluster i , and μ_i is the centroid of that cluster.

For each image, six dominant color centroids and their relative proportions were obtained. The normalized color feature vector is written as:

$$C = (w_1, w_2, ..., w_6) \tag{2}$$

where w_i is the proportion of the i -th color cluster.

To describe perceptual contrast among dominant colors, pairwise color differences were further calculated using the CIEDE2000 formula [8]. The average intra-image color-difference value was used as a descriptor of visual contrast intensity.

Pattern features were extracted using the Canny edge detection method [7]. The resulting binary edge maps were analyzed with reference to classical texture descriptors [8]. To improve reproducibility, two quantitative pattern indicators and one categorical directional descriptor were retained in the final framework.

First, pattern density was defined as:

$$D = \frac{N_{edge}}{N_{total}} \tag{3}$$

where N_{edge} is the number of detected edge pixels and N_{total} is the total number of pixels.

Second, edge component count was used as a descriptor of structural fragmentation. It was defined as the number of connected edge regions in the binary edge map after removing isolated noise pixels smaller than 10 pixels.

Third, dominant orientation category was identified from gradient orientation statistics and classified into four categories: horizontal, vertical, oblique, and radial-dominant. This descriptor was used as a high-level visual organization cue for motif arrangement in the later design translation stage, rather than as a direct determinant of garment structure or layout generation.

For the silk scarf group, all schemes were generated in a square format of 90 cm × 90 cm. For the evening dress group, the same prototype features were translated into garment surface layout, pattern concentration zones, and symmetry tendency. To reduce potential confounding effects, all schemes were generated under the same digital rendering resolution, material assumption, and comparable color rendering conditions.

Prototype Construction and Design Translation

The 15 mural images were not translated individually into final design products. Instead, their extracted features were used to construct three representative visual prototypes. Specifically, the images were grouped according to similarity in dominant color composition, average color contrast, pattern density, and dominant orientation. The grouping process combined normalized feature comparison with feature-guided clustering and expert validation to improve both quantitative consistency and visual interpretability. In the present study, expert validation was introduced as an interpretive refinement step to ensure that statistically similar image groups also retained acceptable visual coherence and design readability, rather than to replace the quantitative grouping process itself. As a result, 5 images were assigned to Prototype A, 4 images to Prototype B, and 6 images to Prototype C.

Prototype A exhibited moderate contrast, medium pattern density, and predominantly horizontal organization. Prototype B showed relatively high color contrast, denser motif distribution, and a stronger oblique or mixed-direction tendency. Prototype C presented a more balanced chromatic composition, lower motif density, and clearer radial or center-oriented organization.

Based on these three prototypes, six design schemes were developed, including three silk scarf schemes (S1–S3) and three evening dress schemes (D1–D3). In this way, each silk scarf design and each evening dress design corresponded to the same prototype style, ensuring that comparisons between product categories were based on consistent visual inputs.

A predefined rule-guided mapping strategy was then employed to translate visual features into design parameters. The mapping rules were defined as follows:

- the first three dominant colors, ranked by proportion, were assigned to the primary, secondary, and accent color regions of the design;
- larger average color-difference values corresponded to stronger contrast between major design regions;
- higher pattern density values resulted in greater motif coverage in the textile layout;
- the dominant orientation category was used as a compositional reference for motif distribution and directional emphasis, such as border-like repetition for horizontal-dominant prototypes and center-oriented visual composition for radial-dominant prototypes.

The orientation descriptors were not directly converted from pixel-level gradients into garment construction parameters. Instead, they were used as abstract visual cues to support compositional organization during the design translation process. This translation strategy was heuristic rather than uniquely determined. However, the rules were specified before design generation and applied consistently across all schemes to improve transparency and reproducibility.

For the silk scarf group, all schemes were generated in a square format of 90 cm × 90 cm. For the evening dress group, the same prototype features were translated into garment surface layout, pattern concentration zones, and symmetry tendency. To reduce potential confounding effects, all schemes were generated under the same digital rendering resolution, material assumption, and comparable color rendering conditions.

Evaluation Method and Sensitivity Analysis

To assess the generated design schemes, a multi-criteria evaluation framework was established based on five criteria: cultural expression, aesthetic quality, design innovation, practical applicability, and perceived market acceptance. In the present study, "practical applicability" mainly referred to visual adaptability and compositional usability in contemporary textile and apparel products, rather than engineering-level garment manufacturability or ergonomic performance.

The weights of these criteria were determined using the Analytic Hierarchy Process (AHP), a widely used method in multi-criteria decision-making applications [11,14]. Ten experts participated in the evaluation, including four specialists in textile design, three in fashion design, and three in cultural heritage studies. All experts had at least five years of relevant academic or professional experience. Each expert completed the pairwise comparisons independently, and the final comparison matrix was obtained by geometric averaging of the individual judgments.

The consistency index and consistency ratio were calculated as:

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{4}$$

$$CR = \frac{CI}{RI} \tag{5}$$

The maximum eigenvalue of the final comparison matrix was $\lambda_{max} = 5.21$, giving $CI = 0.0525$ and $CR = 0.0469$. Since $CR < 0.1$, the matrix was regarded as acceptably consistent.

The final AHP weight vector was:

- cultural expression: 0.29

- aesthetic quality: 0.23
- design innovation: 0.17
- practical applicability: 0.16
- perceived market acceptance: 0.15

To account for uncertainty in subjective scoring, fuzzy set theory was introduced [12], and fuzzy multiple attribute decision making was employed to synthesize the expert evaluations [13]. A five-level linguistic scale was adopted, including very low, low, medium, high, and very high. The corresponding numerical ranges were converted into fuzzy membership values to construct the evaluation matrix R . Let W denote the AHP weight vector and R denote the fuzzy evaluation matrix. The final evaluation result is expressed as:

$$B = W \cdot R \tag{6}$$

For sensitivity analysis, each criterion weight was increased and decreased by 10% in turn, while the remaining weights were proportionally renormalized so that the total sum remained equal to 1. This procedure generated 10 single-factor perturbation scenarios in addition to the baseline configuration. The purpose was to determine whether moderate variations in criterion importance would substantially affect the ranking of the design schemes.

RESULTS AND DISCUSSION

Feature Extraction Results and Prototype Construction

Color Feature Results

The 15 mural images showed a clear concentration of color usage. After K-means clustering with $k = 6$, the average proportion of the top three dominant colors was 70.8% ± 5.3%, indicating that the selected mural images generally exhibited hierarchical rather than uniform color organization. However, the variation across samples was not negligible, ranging from 63.9% to 78.6%. This suggests that some images showed stronger dominance of the primary color groups, whereas others retained a relatively more distributed chromatic composition.

The average intra-image CIEDE2000 distance among dominant colors was 17.9 ± 3.1, with observed values ranging from 13.8 to 23.4. This result indicates moderate variation in color contrast. Some mural images exhibited relatively harmonious palettes with lower color-difference values, whereas others showed stronger contrast between dominant and accent colors.

Pattern Feature Results

The average pattern density of the 15 images was 0.176 ± 0.028. The lowest values were observed in mural fragments with larger plain background regions, whereas the highest densities occurred in samples containing denser ornamental repetition. The average edge component count was 124 ± 31, indicating noticeable variation in structural fragmentation across the selected images.

In terms of dominant orientation, 6 images were classified as horizontal-dominant, 2 as vertical-dominant, 4 as oblique-dominant, and 3 as radial-dominant. This distribution suggests that Dunhuang mural patterns do not conform to a single spatial organization mode, which further supports the need to distinguish multiple visual prototypes for design translation. These variations in density, structural fragmentation, and orientation provided the quantitative basis for subsequent prototype construction.

Prototype Construction Results

Based on the extracted color and pattern features, the 15 mural images were grouped into three representative prototypes using feature-guided grouping with expert validation. The grouping process considered dominant color concentration, average color contrast, pattern density, and dominant orientation category.

Prototype A included 5 images and was characterized by moderate color contrast, medium pattern density, and horizontal-dominant organization. Prototype B included 4 images and showed the highest average color contrast and motif density, together with a stronger oblique or mixed directional tendency. Prototype C included 6 images and exhibited a more balanced color composition, lower average motif density, and a clearer radial or center-oriented arrangement.

Quantitatively, Prototype B displayed the highest average contrast and density among the three groups, whereas Prototype C showed the lowest average density and a relatively more ordered spatial organization. Prototype A remained between these two groups and represented a comparatively moderate visual type. This grouping result is consistent with the quantitative feature distribution extracted from the original mural images.

These three prototypes were then used as the visual basis for subsequent design generation. Specifically, silk scarf schemes S1–S3 and evening dress schemes D1–D3 were developed based on the features of Prototypes A–C, respectively, so that cross-category comparison could be conducted under comparable prototype conditions.

Design Translation Results

The six generated design schemes preserved the main visual characteristics of their corresponding prototypes, although differences emerged between product categories because of distinct functional and compositional requirements. The design schemes derived from the three prototypes are presented in Figure 2.

Figure 2. Design schemes (silk scarves S1–S3 and evening dresses D1–D3) derived from the three prototypes

For the silk scarf group, the translation of mural features was generally more direct. Compared with evening dresses, the scarf schemes retained larger motif coverage and stronger border repetition, particularly in S2, which was derived from the denser and higher-contrast Prototype B. This made the cultural reference more visually explicit, but also increased overall visual complexity.

For the evening dress group, the translation process was more selective. Although the same color hierarchy and motif characteristics were retained, the patterned areas were more concentrated in structurally appropriate garment zones, such as the hem, waist-adjacent areas, or upper decorative regions. For example, D3, based on Prototype C, adopted a more center-oriented and balanced motif arrangement, which improved visual order while still preserving recognizable cultural features.

Cross-category comparison within the same prototype further indicates that product type affects the intensity of feature retention. For example, S2 and D2 shared the same high-density prototype input, but the patterned area had to be moderated in D2 to avoid excessive visual burden on the garment surface. By contrast, S3 and D3, both informed by Prototype C, benefited from the lower-density and more ordered visual basis, which supported clearer composition and better adaptability.

These results indicate that extracted mural features cannot be transferred to different products with identical intensity. Instead, product function constrains the final range of translation, particularly with regard to pattern density and motif arrangement.

Evaluation Results

AHP Weight Results

The AHP analysis assigned the highest weight to cultural expression (0.29), followed by aesthetic quality (0.23), design innovation (0.17), practical applicability (0.16), and perceived market acceptance (0.15). This distribution indicates that the experts placed the greatest emphasis on cultural fidelity, while still considering visual quality and product usability as important dimensions in the overall evaluation.

Because the consistency ratio was 0.0469, the resulting weight structure was regarded as acceptably reliable for the subsequent evaluation.

Comprehensive Evaluation Results

The fuzzy comprehensive evaluation results are shown in Table 1.

Table 1. Evaluation Results of the Six Design Schemes (Mean ± SD)

Scheme	Cultural	Aesthetic	Innovation	Practicality	Market	Overall
S1	80.9±3.1	79.2±2.8	77.4±3.0	81.0±2.3	78.8±2.7	79.6±2.5
S2	85.4±2.4	77.8±3.7	78.9±2.9	73.6±4.1	75.8±3.6	78.4±2.9
S3	78.6±2.8	83.5±2.4	81.1±2.2	84.0±2.0	82.3±2.5	81.7±2.1
D1	79.4±2.6	80.8±2.7	77.9±2.5	82.1±2.4	81.0±2.3	80.3±2.2
D2	84.1±2.7	78.6±3.2	79.1±2.8	75.4±3.8	76.9±3.1	78.6±2.7
D3	80.2±2.5	83.3±2.2	81.5±2.1	83.1±2.1	82.6±2.4	81.9±2.0

Among the six schemes, D3 achieved the highest overall score, followed closely by S3. Although these two schemes did not obtain the highest scores in cultural expression, they demonstrated the most balanced performance across aesthetic quality, practical applicability, and perceived market acceptance. This suggests that moderate retention of mural features, combined with clearer visual order, may lead to more favorable overall evaluations.

By contrast, S2 and D2 achieved the highest scores in cultural expression but lower scores in practical applicability and perceived market acceptance. The higher motif density and stronger visual contrast associated with Prototype B appeared to enhance the recognizability of cultural features, but also increased visual complexity and reduced visual adaptability and compositional usability in contemporary product contexts.

Trade-off Discussion

The evaluation results reveal a clear trade-off between cultural feature retention and practical usability. Schemes derived from the denser and higher-contrast prototype preserved mural-inspired visual characteristics more strongly, thereby improving cultural expression. However, the same feature combination also increased visual complexity and perceptual load, making the designs less adaptable in practical product contexts. It should be noted that the rule-guided translation strategy was not intended to directly maximize all extracted mural features. High color contrast and dense motif distribution were treated as indicators of stronger cultural feature retention, but their direct transfer into product design could reduce visual adaptability and perceived market acceptance.

By contrast, schemes derived from the more balanced Prototype C did not maximize cultural richness, but achieved better overall performance due to improved compositional clarity and functional suitability. This finding suggests that effective cultural translation in design should not be interpreted as the direct maximization of extracted features. Instead, more desirable outcomes can be achieved through the selective preservation and structured reorganization of cultural features in accordance with product-specific constraints.

Sensitivity Analysis

The baseline ranking of the six schemes was:

$$D3 > S3 > D1 > S1 > D2 > S2 \tag{7}$$

After applying the 10 single-factor perturbation scenarios, D3 remained the best-performing scheme in all cases, and S3 also exhibited high ranking stability. By contrast, the relative positions of D1 and S1, as well as D2 and S2, changed slightly under certain perturbation conditions.

When the weight assigned to cultural expression was increased, S2 and D2 improved their relative positions because these schemes preserved denser and more explicit mural features. Conversely, when the weights of practical applicability or perceived market acceptance were increased, S3 and D3 became more advantageous, reflecting their more balanced visual adaptation.

Across the six schemes, score variations were observed after the ±10% weight perturbations, particularly for S2 and D2, which had stronger cultural-expression characteristics. When the weight of cultural expression increased, these two schemes showed more noticeable score changes than the more balanced schemes. Therefore, the sensitivity analysis should be interpreted as evidence of relative ranking stability for the top-performing schemes, rather than as proof that the overall scores were insensitive to weight adjustment. Overall, the results suggest that the evaluation model allows reasonable variation under different design priorities while maintaining a relatively consistent ranking of the leading schemes.

Discussion of Methodological Scope

Although the proposed framework improves the transparency and quantitative support of cultural design translation, several limitations should be acknowledged. First, the number of mural images and generated design schemes remains limited. Therefore, the present study should be interpreted as a structured exploratory validation rather than a fully generalizable large-sample model. Second, perceived market acceptance was evaluated by experts rather than through direct consumer testing. Although this approach is acceptable for preliminary comparative assessment, future studies may strengthen the evaluation framework by incorporating user-based experiments or consumer survey data. Third, the prototype construction process combined quantitative feature comparison with expert validation. While this strategy improves interpretability and design readability, it also retains a certain degree of heuristic judgment. Therefore, the proposed framework should be understood as a semi-structured, expert-assisted translation approach rather than a fully automated or purely objective design-generation system. Fourth, practical applicability in the present framework mainly refers to visual adaptability and compositional usability in contemporary textile and apparel products. Factors such as garment construction, body movement, material behavior, production cost, and wearing comfort were not quantitatively evaluated in this study.

Despite these limitations, the present results still demonstrate that the proposed framework provides a reproducible and analytically supported approach for translating Dunhuang mural color and pattern features into modern textile and garment design. In particular, the integration of image-based feature extraction, prototype-guided translation, and multi-criteria evaluation offers a feasible methodological basis for improving the consistency and evaluability of culturally inspired design. Future research may further extend this framework by increasing sample size, refining prototype construction strategies, incorporating consumer-centered validation, and including garment construction, material behavior, production cost, and wearing comfort in the assessment of practical applicability.

CONCLUSION

This study proposed a structured framework for the translation and evaluation of Dunhuang mural color and pattern features in modern silk scarf and evening dress design. By integrating digital image processing, prototype-based feature aggregation, rule-guided design translation, and AHP–fuzzy comprehensive evaluation, the study aimed to improve the transparency, consistency, and evaluability of culturally inspired textile and apparel design.

The results indicate that the proposed feature extraction approach can effectively capture key visual characteristics of Dunhuang mural images, including dominant color composition, perceptual color contrast, pattern density, and orientation features. Based on these extracted characteristics, three representative visual prototypes were constructed to support the generation of six design schemes. The evaluation results further show that schemes with stronger cultural feature retention tend to achieve higher scores in cultural expression, but often perform less favorably in practical applicability and perceived market acceptance because of increased visual complexity. By contrast, more balanced schemes achieve better overall performance by maintaining a more appropriate trade-off between cultural representation and usability.

Sensitivity analysis further demonstrates that the top-performing schemes remain relatively stable under moderate variations in criterion weights, whereas middle-ranking schemes are more sensitive to changes in evaluation priorities. This suggests that the proposed framework is reasonably robust for comparative design assessment.

Overall, the study demonstrates that effective cultural translation in design should rely on selective preservation and structured adaptation rather than direct replication of traditional visual elements. Although the present work is limited by sample size, expert-based evaluation, and the heuristic nature of prototype construction, it provides a reproducible and analytically supported methodological reference for integrating Dunhuang mural visual features into modern textile and apparel products. Future research may extend this framework by using larger datasets, incorporating consumer-centered evaluation, and exploring more automated design generation methods.

Availability of Data and Materials

The datasets used and/or analysed during the current study were available from the corresponding author on reasonable request.

Author Contributions

Xiaochen Shen designed, collected and analyzed the data, and drafted the manuscript. Xiaochen Shen conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Xiaochen Shen participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

Conflict of Interest

The author declares no conflict of interest.

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