International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18 (2026) pp. 1-13

https://doi.org/10.70917/ijcisim-2026-2307
Article

A Study on the Digital Extraction and Semantic Coding of Color Genes in Intangible Cultural Heritage, and AI-Driven Pathways for Innovative Derivative Design

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Abstract: The rapid development of digital media technology has opened up entirely new avenues for the extraction of color genes from intangible cultural heritage (ICH) and the creation of derivative designs. Prior to extracting color genes from ICH, the ICH RGB color space must be converted to the HSV color space, after which the K-Means clustering algorithm is applied to digitally extract the ICH color genes. Next, based on semantic theory, the extracted color genes are semantically encoded. Subsequently, genetic algorithms—a technique from artificial intelligence—are employed to explore innovative derivative design pathways for these color genes. Finally, by solving the fitness function, the optimal derivative design scheme for a series of cultural and creative products based on these color genes is obtained. When K is set to 5, the K-means clustering algorithm performs optimally, successfully extracting the color genes of intangible cultural heritage and performing semantic encoding on them. Calculations using the genetic algorithm revealed that color scheme 5 and color combination 5 yielded the highest fitness function values, thereby providing the optimal derivative design solutions for a series of cultural and creative products based on ICH color genes. Furthermore, based on the research findings, a design pathway for ICH-derived products is proposed, aiming to provide theoretical guidance for the inheritance and dissemination of intangible cultural heritage.

Keywords: K-means clustering algorithm; genetic algorithm; ICH color genes; semantic encoding

1. Introduction

Intangible cultural heritage is closely related to the daily lives and production of the general public, serving as the anchor point for individual, group and national memories. It is the accumulation of national history, the crystallization of national culture and the symbol of national spirit [1-3]. However, with the advancement of modernization and urbanization and the improvement of the overall level of informationization, traditional artisans are decreasing, and there has been partial interruption of the "cultural memory" of the nation. Intangible cultural heritage is facing serious threats of being forgotten, damaged, and even gradually disappearing [4-7]. The rescue and protection of intangible cultural heritage is urgent [8], especially the color system that symbolizes the emotional expression and philosophical concepts of intangible cultural heritage, which is an important part of the cultural protection project.

With the development of society and the advancement of digital technology, intangible cultural heritage and modern technology present a trend of integration, bringing new forms for the activation, inheritance and innovation of intangible cultural heritage [9-11]. The application of digital technology not only creates a new material world but also brings new social and spiritual realities, and expands in spatial, temporal and social fields [12-14]. Therefore, using digital technology to comprehensively intervene in the management fields such as collection, organization, dissemination and service of intangible cultural heritage resources, and establishing an intangible cultural heritage protection mechanism adapted to the digital age, has become an important development trend in the current protection of intangible cultural heritage [15-17]. In this context, studying the digital extraction of intangible cultural heritage color genes, semantic encoding and AI-driven innovative derivative design paths is of great significance.

Before extracting colors from intangible cultural heritage (ICH), this paper processes them to convert them into a color model that most closely approximates human perception; therefore, RGB values are converted to the HSV color model through mathematical operations. The *K*-Means clustering algorithm is applied to preprocessed ICH images to extract color genes, followed by semantic encoding of these ICH color genes to facilitate subsequent design research. Based on the essence of artificial intelligence technology, this paper proposes using genetic algorithms to explore innovative derivative design pathways for ICH color genes. By solving the fitness function, optimal derivative design schemes for a series of cultural and creative products based on ICH color genes are obtained. Finally, based on the analysis results, three AI-driven pathways for ICH derivative design are formulated, with the aim of promoting the digital dissemination and development of intangible cultural heritage.

2. A Digital Study of the Color Genes of Intangible Cultural Heritage

2.1. K-means Algorithm

Clustering algorithms are among the most commonly used methods in modern data analysis, typically employing *K*-means, fuzzy *C*-means, expected maximization, and average drift algorithms. When applying this method to the extraction of color genes from intangible cultural heritage, the process essentially involves continuous computational processing using computer software to obtain stable cluster centers; these cluster centers then serve as the primary colors to be used.

2.1.1. Principles of the K-means Algorithm

The *K*-means algorithm is a type of partitioning clustering method that readily produces optimal clustering results. Its advantages include the ease of achieving the desired results, high efficiency in processing large amounts of data, and strong versatility. The basic steps of the *K*-means algorithm are as follows:

(1) Select the initial clustering points by arbitrarily filtering from the N imported targets.

(2) After identifying the cluster center A, calculate the Euclidean distance D between the remaining data points and A, and assign each data point to the nearest cluster center $A_i \left(1 \le i \le N\right)$ based on this distance, until all samples are divided into X clusters, ensuring that the characteristics of samples within each cluster are relatively similar, while the differences between clusters are significant. The formula for calculating the Euclidean distance D is given in Equation (1):

$$D = \sqrt{\left(H_1 - H_2\right)^2 + \left(S_1 - S_2\right)^2 + \left(V_1 - V_2\right)^2} \tag{1}$$

Here, H_1, S_1, and V_1 represent the color space values of arbitrary data objects, while H_2, S_2, and V_2 represent the color space values of cluster center A.

(3) After each iteration, select a new cluster center that is furthest from the previous cluster center.

(4) Repeat the above two steps until the specified number of clusters is reached.

2.1.2. Principles for Selecting Cluster Centers

The selection of cluster centers based on the theory of maximum and minimum distances differs from the operation of the traditional *K*-means clustering algorithm. First, an initial cluster center is selected at random. When determining the second cluster center, it is ensured that this second cluster center is the point farthest from the initial cluster center in the entire target dataset, and subsequent cluster centers are identified based on this criterion. The point in the remaining target dataset with the smallest Euclidean distance to the already selected cluster center is added to the set, and the point with the largest distance within the set is designated as the next cluster center. This process is repeated by following the above principles until the number of cluster centers reaches the specified number of iterations.

2.2. Color Gene Extraction Process

2.2.1. Color Space Conversion

Before extracting colors, they must first be processed and converted into a mode that most closely matches human perception. Therefore, RGB values are converted through calculations into the HSV color model—that is, hue, saturation, and value. The HSV color model provides an intuitive representation of grayscale, brightness, and emotional tone, making it well-suited for color processing and editing. The corresponding formulas for converting the RGB color mode to the HSV color space are shown in Equations (2) through (4):

$$H = \begin{cases} 0^{\circ} & \Delta = 0 \\ 60^{\circ} \times \left(\dfrac{G' - B'}{\Delta} \bmod 6 \right) & C_{\max} = R' \\ 60^{\circ} \times \left(\dfrac{B' - R'}{\Delta} + 2 \right) & C_{\max} = G' \\ 60^{\circ} \times \left(\dfrac{R' - G'}{\Delta} + 4 \right) & C_{\max} = B' \end{cases} \tag{2}$$

$$S = \begin{cases} 0 & C_{\max} = 0 \\ \dfrac{\Delta}{C_{\max}} & C_{\max} \neq 0 \end{cases} \tag{3}$$

$$V = C_{\max} \tag{4}$$

In the formula, $R' = R/255$, $G' = G/255$, $B' = B/255$, $C_{\max} = \max\left(R', G', B'\right)$, $C_{\min} = \min\left(R', G', B'\right)$, and $\Delta = C_{\max} - C_{\min}$.

2.2.2. Image Preprocessing

Upon analyzing the image before importing it, we found that its content includes the main pattern as well as other patterns, the background, decorative lines, and so on. If these elements are retained, they will affect the results of the iterative calculations. To improve the accuracy and usability of color extraction, the image is processed before import. The specific steps are as follows:

(1) Import the image to be processed into image processing software. Use the selection tool to remove areas outside the color range of the main pattern to be extracted.

(2) Since MATLAB's processing logic fills areas with no pixels with white, to eliminate the impact of this behavior, fill the blank areas in the image (resulting from the previous step) with a color that contrasts significantly with the pattern to be extracted before the iteration. Additionally, incorporate logic into the iteration code to remove the color that accounts for the largest proportion of pixels (i.e., the fill color).

2.2.3. Color Gene Extraction Based on *K*-Means Clustering

First, the preprocessed images are imported into a MATLAB-based computational logic. Iterative clustering is performed according to the maximum and minimum distance principles to determine the proportion of colors to be extracted from the images. The specific experimental steps are as follows:

(1) Since the number of colors varies from image to image, it is necessary to manually estimate the number of colors in each image before the iteration begins and determine the number of iterations based on this estimate.

(2) By importing the preprocessed images several times for trial runs, the optimal number of iterations is determined based on the results and the desired outcome. After the iterative process is complete, the proportions of the *N* colors are obtained; the fill color is then removed, leaving *N-1* colors.

(3) Classify intangible cultural heritage (ICH) based on different artistic color styles, perform *K*-means clustering on the preprocessed images, and showcase the color characteristics of certain ICH categories with refined and vivid color schemes.

2.3. Semantic Coding of Color Genes

Based on the theoretical foundations of semantic coding, the semantic coding of color genes is related to age. During childhood, people typically prefer objects with striking colors. As they grow older, they tend to focus more on lighter colors. In terms of hue, women prefer red, men prefer blue, and fewer people prefer yellow. In terms of saturation, young people prefer high-saturation colors, while older adults prefer low-saturation colors. Older adults tend to prefer cooler colors, while younger people tend to prefer warmer colors. In terms of brightness, younger people prefer strong, bright colors, whereas older adults prefer soft, subdued colors. The semantic encoding process of color genes is illustrated in Figure 1. Designers encode the color genes of intangible cultural heritage, transforming them into visual symbols or visual symbol systems. Finally, the audience receiving these visual symbols (graphics) interprets the semantics of the intangible cultural heritage and responds with corresponding actions, thereby completing the semantic encoding of the color genes. Specifically, the design objectives, intentions, and meanings are selected and processed by the designer, transformed into design symbols, and thereby manifested externally.

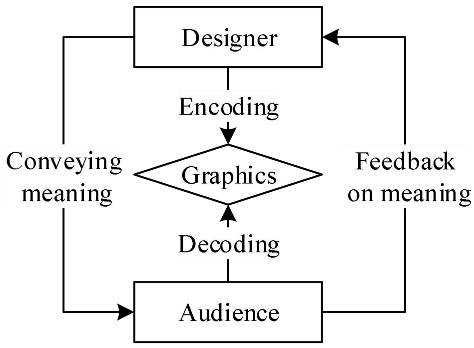

Figure 1. The semantic encoding process of color genes

3. AI-Driven Innovation and Derivative Design Pathways

In the previous chapter, the *K*-Means clustering algorithm was used to digitally extract the color genes of intangible cultural heritage, and semantic theory was applied to encode them, ultimately achieving the digital transformation of these color genes. Building on this foundation, genetic algorithms—a type of artificial intelligence technology—were employed to design a series of cultural and creative products derived from these color genes, with the aim of promoting the digital preservation and dissemination of intangible cultural heritage.

3.1. Genetic Algorithms

3.1.1. Fundamental Theory

In the field of artificial intelligence, genetic algorithms (GA) are computational models that mimic the biological evolutionary process—specifically, the mechanisms of natural selection and genetics as described in Darwin’s theory of evolution. They are a method for finding optimal solutions by simulating natural evolutionary processes; the basic process of biological evolution is illustrated in Figure 2. The basic principle of genetic algorithms is to refer to a single solution to a design problem—such as the derivation of a series of cultural and creative products featuring non-heritage-themed color schemes—as a “chromosome,” and to refer to a set of such solutions as a “population.” The process begins with the evolution of a randomly generated initial biological population; chromosomes continuously mate during subsequent iterations of the algorithm to produce the next generation, and the resulting chromosomes are referred to as “offspring.”

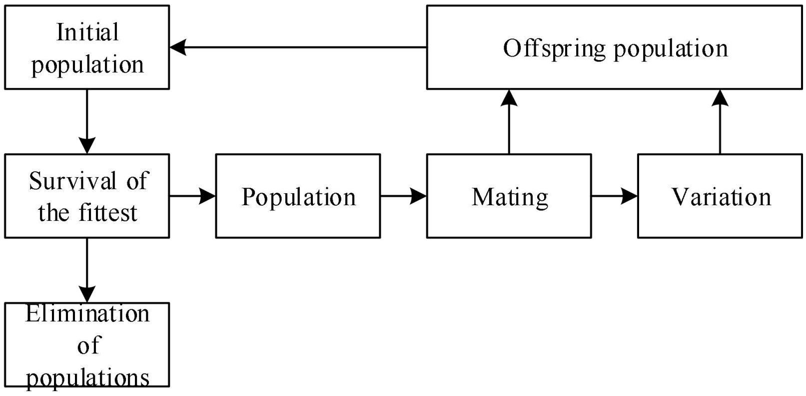

Figure 2. The basic process of biological evolution

3.1.2. Applications of Genetic Algorithms

Genetic algorithms are being increasingly applied in the field of innovative derivative design for intangible cultural heritage. Through the computational processes of crossover and mutation, these algorithms generate new individuals. Since they do not follow fixed rules, they are highly likely to produce offspring that differ significantly from their parents. Such results help designers broaden their thinking and meet the requirements for innovation during the design phase of intangible cultural heritage derivative products.

3.2. Genetic Algorithm-Based Design Derived from the Color Genes of Intangible Cultural Heritage

3.2.1. Initial Sample Screening

The iteration of the "Intangible Cultural Heritage Color Genes" series of cultural and creative products is based on an understanding of market trends; objectively, it depends on adaptability to environmental and seasonal factors, while subjectively, it depends on user preferences and prevailing trends. By screening samples of the "Intangible Cultural Heritage Color Genes" series of cultural and creative products from the past five years, we have selected samples with excellent genetic traits and distinct characteristics that demonstrate high market adaptability to serve as initial samples in the genetic algorithm, thereby enhancing the innovation of derivative product designs that incorporate these intangible cultural heritage color genes.

3.2.2. Genetic Chromosome Coding

The color-matching genetic code chromosome consists of design elements and color values for intangible cultural heritage (ICH) cultural and creative products, defined as $\{\{F1,B1\},\{F2,B2\},\{F3,B3\},\cdots,\{F_n,B_n\}\}$. Here, F_i represents the i th color scheme for ICH cultural and creative products, which also serves as a static attribute of the chromosome and remains stable during genetic operations. B_i represents the i th color gene $B_i:\{H,S,B\}$, which, as a dynamic attribute, undergoes iterative updates during genetic operations. This method of numbering based on chromosomal structural attributes not only ensures flexibility in genetic operations but also allows for direct manipulation of color components.

3.2.3. Fitness Function Construction

The fitness function serves as the objective function for selecting the best individual. By constructing an evaluation model, the best chromosome is identified to generate the highest score.

(1) Color Scheme Evaluation for Intangible Cultural Heritage (ICH) Derivative Products

In the design process of ICH-derived cultural and creative products, the distribution ratio of cool and warm colors is a key factor influencing the product's visual impact and reflects the relationship between area and color. Therefore, an evaluation of the color distribution in a product's color scheme can be constructed based on the ratio of cool to warm color areas. The formula is as follows:

$$y = \frac{Sl}{Sn} \tag{5}$$

Here, Sl represents the area of cool colors, Sn represents the area of warm colors, and the range of values for y is the set of ratios obtained in the two cases where the area of cool colors in the sample is greater than the area of warm colors and where the area of warm colors is greater than the area of cool colors.

(2) Model for Evaluating the Aesthetic Quality and Harmony of Design Schemes

Aesthetic quality refers to the degree of success in color coordination. By using aesthetic quality evaluation to constrain color harmony, the aesthetic quality of product color design schemes can be enhanced. In the Mido calculation formula, M stands for Mido, O stands for the order factor, and C stands for the complexity factor. That is:

$$M = o/c \tag{6}$$

This quantitative formula was also applied to the evaluation of color schemes. Based on experimental results, it was determined that the order factor takes on different values depending on whether or not color is involved in the color scheme. That is:

$$O = \sum Og \tag{7}$$

$$O = \sum Oh + \sum Ov + \sum Oc \tag{8}$$

Og represents the order factor when the color scheme consists solely of achromatic grays; Oh, Ov, and Oc represent the respective order factors when chromatic colors are included in the color scheme, determined solely by differences in hue, value, or saturation, respectively, and their values depend on the intervals between the various color attributes. The complexity factors are composed as follows:

$$C = Cm + Ch + Cv + Cc \tag{9}$$

Cm represents the total number of colors in a color scheme, defined as the number of color pairs among all possible combinations that differ in hue; Ch represents the number of color pairs among all possible combinations that differ in value; and Cv represents the number of color pairs among all possible combinations that differ in saturation.

(3) Comprehensive Evaluation Model

When developing the comprehensive evaluation model, the relative weights of the aesthetic harmony evaluation model and the color scheme evaluation model for cultural and creative products derived from intangible cultural heritage should be taken into account; therefore, appropriate weightings should be assigned to them. a represents the weighting coefficients for the Mido Harmony Evaluation Model, and b represents the weighting coefficients for the color scheme evaluation of brand extension products. Designers can set different weightings as needed. This results in a comprehensive evaluation model based on the principles of color aesthetics and defined target requirements. The evaluation score for the color scheme generated by this model is F. That is:

$$F = aN + bM,\ a,b \in [0,1] \tag{10}$$

In the formula: N —the harmony rating for warm and cool colors in the design.

M —the harmony rating.

a, b —the weight; this value can be flexibly adjusted according to design requirements.

3.2.4. Genetic Algorithm Operations

(1) Constraints

In addition to the logical relationships among the physical parameters of the samples themselves, constraints must also be placed on the range of color selections within the color scheme series. These constraints include the HSV value range of the color scheme based on market adaptability requirements and the color area ratios of the color scheme based on color composition.

(2) Population Size

The size of the population directly determines the computation time per generation, while the number of evolutionary generations determines the accuracy of the optimization solution. Since this paper involves a large number of design variables, the initial population size must first be determined. The initial population can be obtained by selecting values within the permissible ranges for color schemes and color relationships in cultural and creative products based on the “Intangible Cultural Heritage Color Genes” series.

(3) Selection Operation

The method employed in this paper involves using computational algorithms to identify individuals with higher fitness, which serve as the genetic foundation for the next generation of the population. From the parent population, color scheme design features of cultural and creative products associated with intangible cultural heritage color gene series that receive relatively high overall evaluations are selected. These excellent color gene characteristics are then passed on to the next generation, ensuring that the individuals in the next generation carry color scheme features derived from these excellent genes.

(4) Crossover Operation

Select any of the better chromosomes from the sample as crossover candidates, randomly generate one or more crossover points, and exchange color genes to generate new individuals. Throughout this process, because there are correlations among the color attributes in the product’s color genes, crossover must be performed in groups to avoid situations where parameters cannot be matched after the color genes are exchanged. The crossover probability is:

$$Pc = \begin{cases} Pc1\dfrac{(Pc1\cdot Pc2)(f - fm)}{f\max\cdot fm} & f > fm \\ Pc1 & f < fm \end{cases} \tag{11}$$

Here, f represents the fitness of the individuals to be crossed, fm represents the average fitness of the population, $f\max$ represents the maximum fitness of the population, and $Pc1$ and $Pc2$ are probability constants.

(5) Mutation Operation

Since the total population size is limited and further reduced after selection, local optima may occur in the exchange of color genes within the population. Therefore, mutation involves randomly generating new genes with a certain probability when creating new individuals, in order to maintain the diversity of color genes in the population. Mutation operations are controlled by the mutation probability parameter, which typically ranges 0.000001~0.1. Depending on the encoding method, the corresponding mutation operation is applied. The mutation probability is:

$$Pm = \begin{cases} Pm1\dfrac{(Pm1\cdot Pm2)(f - fm)}{f\max\cdot fm} & f > fm \\ Pm1 & f < fm \end{cases} \tag{12}$$

f represents the fitness of an individual awaiting mutation, fm represents the average fitness of the population, $f\max$ represents the maximum fitness of the population, and $Pm1$ and $Pm2$ are probability constants.

(6) Optimal Results

Since the genetic algorithm replaces the worst individuals in the next generation with the best individuals generated in each generation, the more iterations there are, the higher the color saturation of the generated design schemes becomes, ultimately yielding the optimal series of derivative design schemes for cultural and creative products based on the intangible cultural heritage color gene series.

4. In-Depth Exploration

4.1. An Exploration of the Color Genes of Intangible Cultural Heritage

This subsection uses the traditional clothing of the Liangshan Yi people as an example of intangible cultural heritage. Through in-depth case study analysis, it verifies the effectiveness of the *K*-Means clustering algorithm and semantic theory in extracting color genes and performing semantic encoding for intangible cultural heritage. The specific research process is outlined below:

4.1.1. Color Gene Extraction and Analysis

(1) Determining the Optimal Number of Clusters

Another important parameter of the K-means clustering algorithm is the determination of the value of K, that is, the number of clusters. If K is too small, there will be too few clusters, and the differences among samples will be too great; if K is too large, there will be too many clusters, and the differences among samples will be too small. In previous studies on color clustering, the value of K could be determined through manual observation. Alternatively, unsupervised machine learning can be used to find the optimal value of K. The goal of clustering is to minimize the sum of squared errors (SSE) for the distance from each data point to its nearest cluster center. The SSE is calculated as shown in Equation (13):

$$SSE = \sum_{i=1}^{k} \sum_{x \in C_i} \left| d\left(x, C_i\right) \right|^2 \tag{13}$$

Based on the trend in SSE for different K values, at a certain K value, the degree of clustering for each cluster no longer improves significantly—that is, SSE no longer decreases significantly—and this K value represents the optimal solution.

In this subsection, we convert the RGB color space of Yu Opera images to the HSV color space and apply it to the K-means clustering algorithm to determine the optimal number of clusters. Figure 3 shows a line graph of the relationship between the K value and the SSE value. Based on the data presented in the figure, it can be seen that the SSE value is minimal when K is set to 5, indicating that the optimal number of clusters for the extraction of color genes from intangible cultural heritage is 5.

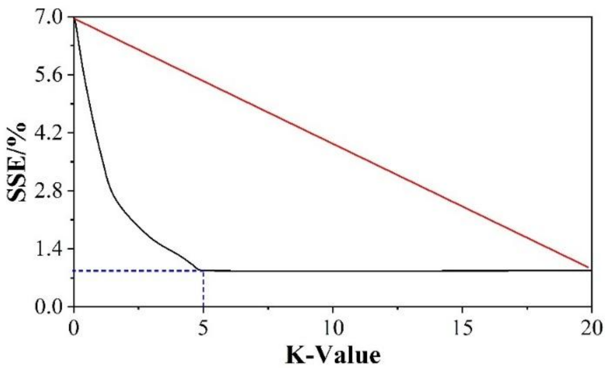

Figure 3. Line graph of K value and SSE value

(2) Results of Cluster Visualization Analysis

Based on the determination of the optimal number of clusters, we proceeded to extract the color genes of intangible cultural heritage. The results of the cluster visualization analysis are shown in Table 1. As indicated by the data labels in the figure, the K-means clustering algorithm identified five types of intangible cultural heritage color genes, these are black (H: 0, S: 0, V: 0), red (H: 0, S: 255, V: 128), yellow (H: 32, S: 253, V: 136), white (H: 0, S: 0, V: 255) , and blue (H: 170, S: 255, V: 128). Their respective color proportions are 27.3%, 23.3%, 21.6%, 15.0%, and 12.8%. The K-means clustering algorithm provides a visual representation of the distribution of color genes in intangible cultural heritage.

Table 1. Visualization analysis results of clustered color clusters

Name	H	S	V	Proportion
Black	0	0	0	27.3%
Red	0	255	128	23.3%
Yellow	32	253	136	21.6%
White	0	0	255	15.0%
Blue	170	255	128	12.8%

(3) Color Network

To further validate the credibility of the aforementioned research findings, an intangible cultural heritage (ICH) color network was constructed. The results of the visual analysis of this color network are shown in Figure 4. The lines represent the frequency of co-occurrence between colors; the higher the frequency, the thicker the line and the larger the color point, indicating a higher proportion within the ICH color gene. It was found that within the ICH color gene set, the order is black > red > yellow > white > blue, which aligns with the aforementioned research findings and fully demonstrates the effectiveness of the *K*-means clustering algorithm in the digital extraction of ICH color genes. After extracting the ICH color genes, directly applying the results of *K*-means clustering can further simplify the semantic coding of color genes, thereby improving the efficiency of derivative design for a series of cultural and creative products based on ICH color genes.

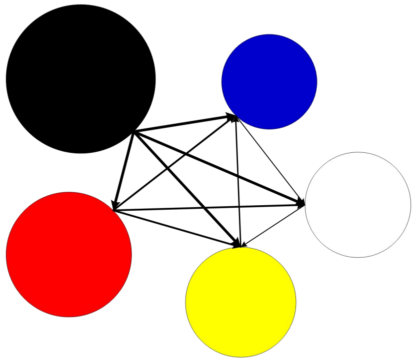

Figure 4. Visualization analysis results of intangible cultural heritage color network

4.1.2. An Analysis of the Semantic Coding of Color Genes

In the process of designing derivative cultural and creative products for the "Intangible Cultural Heritage Color Genes" series, semantic coding is applied to color genes with distinctive Yi ethnic regional characteristics. This ensures that the designs not only convey modern design concepts but also authentically communicate the contemporary information embodied in the products, thereby overcoming the limitations in usage and semantic deviations associated with traditional elements. Consequently, the semantic coding of color genes is indispensable in the design process. Through market research and field visits, it was found that cultural and creative products in the Intangible Cultural Heritage (ICH) Color Gene series generally apply color genes directly to various products without sufficient innovation, which has led to homogenization within this product line. Therefore, by employing semantic coding of ICH color genes to enrich the visual information of these products, the color gene coding for Liangshan Yi ethnic clothing is presented in Table 2. As a symbolic language of intangible cultural heritage, the "color gene" highlights the differences in the Yi people's cultural color genes—as reflected in aspects such as age, social status, and gender—and also reveals the underlying distribution characteristics of these color genes within Yi culture. The overall presentation exhibits characteristics such as solemnity, grandeur, depth, simplicity, elegance, nobility, charm, refinement, brightness, vibrancy, liveliness, playfulness, rustic charm, solemnity, loose fit, and simplicity, expressing the color genes of Liangshan Yi ethnic clothing—extracted using the *K*-means clustering algorithm—through semantic adjectives that evoke sensory imagery. Overall, the process of designing derivative cultural and creative products in the "Intangible Cultural Heritage Color Genes" series involves using explicit methods to express the color genes inherent in Yi ethnic clothing. This not only lays a theoretical foundation for future research but also enhances the visual expressiveness of these derivative products, thereby helping to steer the development of intangible cultural heritage-inspired design toward greater intelligence and convenience.

Table 2. Color gene Coding of Yi ethnic Costumes in Liangshan

Crowd	Male	Female	Children	Old age
Color gene	Black (H:0, S:0, V:0) Red (H:0, S:255, V:128) Blue (H:170, S:255, V:128)	Black (H:0, S:0, V:0) Red (H:0, S:255, V:128) Yellow (H:0, S:255, V:128) White (H:32, S:253, V:136) Blue (H:170, S:255, V:128)	Black (H:0, S:0, V:0) Red (H:0, S:255, V:128) White (H:32, S:253, V:136)	Black (H:0, S:0, V:0) Blue (H:170, S:255, V:128)
Semantics	Solemn, Majestic, Deep and profound, Simple and elegant	Generous, Noble, Charming and alluring, Elegant, Bright and cheerful	Gorgeous, Lively, Fun	Ancient and simple, Solemn, Loose, Plain and clean

4.2. A Study on AI-Driven Design Pathways for Intangible Cultural Heritage Derivatives

4.2.1. Design Case Studies

Using the design of an electric razor that incorporates color elements from intangible cultural heritage as a case study, this paper primarily employs genetic algorithms to analyze the case. The results of the case analysis are described in detail below:

Figure 5 shows the initial population determined based on color elements from intangible cultural heritage; this method uses the *K*-means clustering algorithm described above to extract these color elements. Next, using the color's coordinates in the HSV color space as the center, the color value is expanded by 15.72% in three directions. If the expanded color solution space exceeds the full HSV color space, the excess portion is ignored during encoding. The population size was set to 35, meaning that 35 solutions are generated and decoded for selection each time.

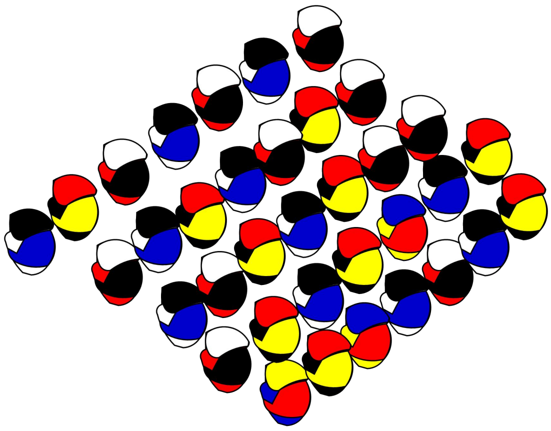

Figure 5. The initial population of the color scheme

To ensure the reliability of the design proposals, a user group was organized consisting of both designers and general consumers. This group included four designers and six general consumers. Drawing on the aforementioned theory, fitness function values were obtained. During the program's execution, users interactively selected proposals; the program automatically recorded the serial numbers of the users' selections, read their codes, and performed statistical analysis.

To ensure that the genetic algorithm searched the solution space as comprehensively as possible, 10 initial populations were randomly generated during the experiment. The design scheme for the electric shaver incorporating intangible cultural heritage colors included 5 color options, while the target scheme included 2 color options. Therefore, there were 10 possible color combination patterns for the target scheme, namely $C_5^2 = \frac{5\times 4}{2\times 1} = 10$. After the initial population was selected, a statistical analysis was conducted on the fitness function values of the color combination patterns. The fitness function values for each color scheme are shown in Table 3. As can be seen from the data in the figure, the fitness function value for Pattern 5 is significantly higher than that of the other nine patterns. Therefore, all subsequent offspring solutions were generated based on Pattern 5, thereby eliminating the noise from the solutions. Figure 6 shows the new set of color schemes generated based on Pattern 5.

Table 3. The fitness function values of each color matching mode

Mode	**Fitness function values**	**Mode**	**Fitness function values**
1	44	6	63
2	25	7	53
3	75	8	49
4	66	9	32
5	88	10	51

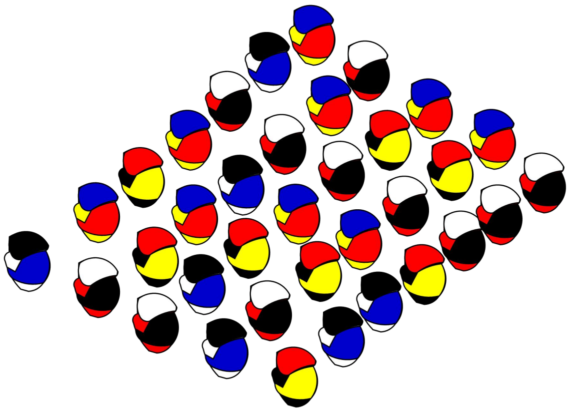

Figure 6. A group of color schemes based on Pattern 5

Finally, to determine users' preferences for color gene combination patterns, 10 rounds of interactive selection were conducted, followed by the calculation of the fitness function for the color combination patterns, as shown in Table 4. The analysis results show that color combination pattern 5 has the highest fitness value, suggesting that this pattern generally provides a superior visual experience for users compared to the other patterns. In the design process of an electric shaver incorporating intangible cultural heritage (ICH) color genes, once both the color scheme and color combination pattern have been determined, the subsequent optimization process focuses primarily on subtle variations in each color. Figure 7 shows the set of color schemes generated during the genetic algorithm implementation. These schemes were constructed by applying subtle variations to the ICH color elements based on the selected color scheme and color combination patterns. Since the color schemes are identical in terms of encoding at this stage, the genetic algorithm can be used to perform operations such as crossover and mutation on the encodings. By evaluating the fitness function, the optimal electric shaver design incorporating ICH color elements is obtained.

Table 4. The fitness function values of different combination modes

Mode	Fitness function values	Mode	Fitness function values
1	35	6	44
2	27	7	24
3	49	8	63
4	48	9	27
5	73	10	31

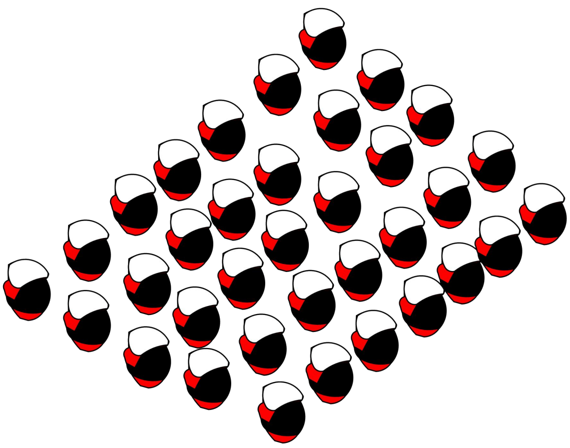

Figure 7. A group of color schemes in the implementation process of genetic algorithms

4.2.2. Developing a Design Pathway for Intangible Cultural Heritage Derivatives

Based on the above research findings, a design framework for deriving color elements from intangible cultural heritage (ICH) can be established. This framework primarily comprises deep structure, surface structure, and structural combination techniques, and aims to provide theoretical support for research on innovative design pathways for ICH color genes within the context of artificial intelligence. The specifics are described as follows:

(1) The process begins with extracting cultural connotations from deep structures to identify color genes, followed by the selection of inheritance types. This process transforms the connotations of observed and collected phenomena into meaningful insights. At this stage, artificial intelligence technology is used to extract specific color genes from ICH, such as the commonly used colors black, red, yellow, white, and blue, which can be categorized into four types: adaptation and refinement, restoration and reconstruction, reproduction, and visualization.

(2) The surface structure—which serves as the vehicle for the deep structure—is constructed in two ways: direct selection of the vehicle and reconstruction of the vehicle. One approach involves selecting existing objects and using artificial intelligence technology to directly integrate them as vehicles for the color genes of intangible cultural heritage. The other approach involves using artificial intelligence technology to design entirely new forms that integrate with the color genes of intangible cultural heritage—that is, reconstructed vehicles.

(3) Structural Combination Techniques

At this stage, "rhetorical techniques"—derived from linguistics—are employed as a key design method in the transformation phase of the design thinking process. Combined with brainstorming, these two approaches serve as structural combination techniques for the innovative derivative design of ICH color genes. This combination not only provides a ready-made, referenceable, and stable transformation model but also endows the derivative design of ICH color elements with greater flexibility and vitality.

5. Conclusion

This paper first uses the *K*-means clustering algorithm to identify the color genes of intangible cultural heritage (ICH) and then encodes them using semantic theory, thereby laying a theoretical foundation for subsequent research. Building on this, genetic algorithms—a technique from the field of artificial intelligence—are employed to explore design pathways derived from these ICH color genes. The research findings of this paper are as follows:

(1) The *K*-Means clustering algorithm successfully extracted the color genes of intangible cultural heritage, which are black (H: 0, S: 0, V: 0), red (H: 0, S: 255, V: 128), yellow (H: 32, S: 253, V: 136), and white (H: 0, S: 0, V: 255), and blue (H: 170, S: 255, V: 128). These ICH color genes were then semantically encoded, revealing the following semantic characteristics: solemn, majestic, profound, simple and elegant, dignified, noble, charming, refined, bright, vivid, lively, whimsical, rustic, solemn, relaxed, and unadorned.

(2) The results of the optimization using a genetic algorithm show that Color Scheme 5 has the highest fitness function value, and Color Combination Scheme 5 also has the highest fitness value. Additionally, visualization results of the ICH-derived designs based on the genetic algorithm are provided. It is evident that in this process, genetic algorithms can be used to perform operations such as crossover and mutation on the semantic encoding of color genes, followed by solving the fitness function to obtain the optimal electric shaver design that integrates ICH color genes. Finally, based on the results of the design case analysis, a design pathway for ICH-derived designs was established, with the aim of achieving the digital and intelligent transmission of ICH culture.

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