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Personalized packaging innovation driven by the integration of digital printing and computer vision

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Abstract This paper proposes a personalized packaging solution integrating digital printing technology and computer image fusion for the problems of low data collection efficiency, insufficient image processing accuracy and high printing customization cost in traditional packaging design. Based on big data analysis, a consumer preference model is constructed, and a K-mean clustering algorithm is used to extract packaging design features. The RTV model and GrabCut algorithm realize image smoothing and accurate segmentation, and combine with digital printing technology to complete high-precision variable data output. In the performance test, after 50 frames of target images are processed by this paper's image processing algorithm, the mean value of Y-value of all target images after processing is 0.957, and the information deviation is always controlled within 5μrad. The average airtightness pass rate of this paper's solution reaches 99.987%, and the control group is reduced by more than 0.4% compared with this paper's solution. The top five satisfaction rankings in formal practice account for three of the desired demand attributes, and the basic demand attributes have lower satisfaction rankings except for local characteristics.

Index Terms personalized packaging, digital printing technology, K-mean clustering, RTV model, GrabCut algorithm

I. Introduction

With the rise of e-commerce and the evolution of consumer demand, consumers are gradually becoming more in pursuit of quality, personalization and emotional experience, and they pay more attention to aspects such as health, environmental protection, and brand values, which prompts companies to provide more diversified products and services to meet these needs [1], [2]. Among them, product packaging has also become the focus of consumer attention. While the initial role of packaging is to protect commodities from being damaged during transportation, the function of packaging is now not only to protect commodities, but also to directly influence consumers' product perception and purchasing behavior [3], [4]. A study shows that more than 50% of consumers are willing to buy goods for personalized packaging [5]. Through personalized packaging design that conveys brand values, companies and brands can better meet consumers' individual needs and thus build consumer loyalty to the brand [6], [7]. The traditional printing process, however, has significant limitations in terms of productivity, print quality, fluctuating demand, and cost [8].

Digital printing technology, compared with the traditional offset printing, flexographic printing, etc., without the need to produce complex printing plates, can produce high-quality prints in a shorter period of time, creating more possibilities for printing companies [9], [10]. It can easily realize the printing of complex patterns and textures, providing more possibilities for packaging design, creating a unique appearance and improving the market competitiveness of products [11], [12]. In addition, digital printing technology can achieve one-to-one personalized packaging production to meet consumers' individual needs [13]. As for computer imaging technology, the automatic and efficient generation of packaging design solutions can be realized through generative artificial intelligence, and the product style can also be replicated. The use of three-dimensional rendering, virtual display of packaging design effects, saving the cost of samples [14], [15]. Digital printing technology and computer image technology bring new life to the packaging industry and provide a path for personalized packaging innovation.

In this paper, we first propose a consumer demand analysis method based on K-mean clustering and Hawking statistics to construct a product positioning model covering multiple levels. An image processing framework that synergizes the RTV model and the GrabCut algorithm is developed to realize the design of personalized packaging solutions in combination with digital printing technology. Set up performance tests to verify the performance level of the technologies selected in this paper. Carry out field application practice and collect user demand satisfaction data through questionnaire survey method. Optimize the KANO model to subdivide the importance degree of demand indicators. Evaluate the application effect of this paper's solution based on the user demand satisfaction ranking.

II. Personalized packaging design combining digital printing technology and computer image fusion

Under the dual drive of diversified consumer demand and intensified market competition, personalized packaging has gradually become the core element of product differentiation and competition. Traditional packaging design has limitations such as long data acquisition cycle, insufficient image processing accuracy, and poor printing customization flexibility. In recent years, the integration of digital printing technology and computer vision algorithms has provided new ideas for solving the above problems, but the existing research mostly focuses on the optimization of a single technology, and lacks systematic integration and cross-field collaborative innovation.

II. A. Big data-driven personalized product packaging design approach

II. A. 1) Extracting consumer preference data

In the past, the preliminary work of packaging design included research on products and markets, and most of them used manual methods to collect data, which was time-consuming, costly, and less capable of analysis. In this paper, in the process of obtaining consumer preference data for packaging, we set up a dedicated packaging data collection channel, adopt big data technology and Internet technology to obtain product packaging information, and save the data in accordance with the set data collection and storage format. The specific collection content (format) is as follows: color, packaging material, packaging form, image type, text structure, description mode, and matching situation. This data is used as the basis for preference feature extraction, and the clustering analysis technique in big data technology is used to obtain consumer preference information for packaging. According to the comparison results of clustering methods, this paper chooses K mean clustering method to extract packaging preference elements. Set the number of collected packaging data as A, and randomly select B objects among N data objects, and set B objects as the center of B preference features. Divide all data into multiple preference categories, where O is a data in the i th preference category set Y_i and α_i is the mean of Y_i. The remaining data are distributed according to the distance from the center point until the convergence process is completed, with the distance SSE between each category and the mean:

$$SSE = \sum_{i=1}^{B} \sum_{O \in Y_i} \left\| O - \alpha_i \right\|^2 \tag{1}$$

Among them:

$$\alpha_i = \frac{1}{|Y_i|} \sum_{O \in Y_i} O \tag{2}$$

According to equation (2) the division of preference data can be realized, and to ensure the accuracy of the information division results, the deviation $D(A, \alpha_i)$ of the data information from the preference center is:

$$D(A, \alpha_i) = \left\| O - \alpha_i \right\|^2 \tag{3}$$

In the process of data processing, Eq. (2) and Eq. (3) will be continuously employed to process the collected data until it cannot be categorized. The categorized data will be analyzed by secondary clustering, which will result in the accurate classification of preference information.

II. A. 2) Complete product positioning

In addition to the results of the consumer packaging preference analysis described above, a product positioning segment has been added to this paper. Product positioning focuses on the information positioning of the product, through which the attributes, characteristics, uses, product content and other information of the product can be conveyed to consumers. To realize effective product positioning, it is necessary to locate the consumer group first.

Through the collection and analysis of consumer positioning information, the consumer characteristics of the product can be obtained. In order to ensure the accuracy of product positioning, it is necessary to use Hawking statistics to calculate the collected consumer characteristics. The collected consumer features are set in the form of a set and named as U, i consumer data are extracted in the dataset, and it is guaranteed that the extraction probability of each data in the set U is the same. For each dataset i, find the set of consumer information j with similar meaning and calculate the distance j_n between the two data:

$$j_n = \min\left\{ dist(i_n, r) \right\} \tag{4}$$

Here, i_n is the nth consumer data of dataset i; $dist(i_n, r)$ is the distance between i_n and the center data r in the dataset.

According to equation (4), find the data k_n which is similar in meaning to j_n, i_n and calculate the distance between k_n and j_n and i_n, then we have:

$$k_n = \min\left\{dist(i_n, r), dist(j_n, r)\right\} \tag{5}$$

Combining equation (4) with equation (5) yields the consumer statistic w:

$$w = \frac{\sum_{n=1}^{i} k_n}{\sum_{n=1}^{i} k_n + \sum_{n=1}^{i} j_n} \tag{6}$$

If the consumer feature data in the collected dataset U is uniformly distributed, it indicates that the values of $\sum_{n=1}^{i} k_n$ and $\sum_{n=1}^{i} j_n$ are close to each other, and the value of w is about 0.5; if the data in U is not uniformly distributed, the value of $\sum_{n=1}^{i} k_n$ is much smaller than $\sum_{n=1}^{i} j_n$, and the value of w tends to 0.

According to the result of this analysis, obtain the result of consumer's needs hierarchy analysis. According to Maslow's hierarchy theory, the characteristics and needs of consumers are analyzed, and the needs of consumers are divided into 5 parts, from the lowest level of physiological needs to the highest level of self-actualization, and the most important thing in the packaging design of the product is to pay attention to the physiological needs of consumers. Such as through packaging design, reflecting the designer's humanized care for consumers, to achieve consumer self-worth satisfaction. Therefore, a hierarchical design of the product is needed. In this design, the same product is set into three grades: high, medium and low, to ensure the accurate positioning of consumer needs, and the packaging design of each grade should also be different, so as to realize the differentiation of the product.

II. B.Image Feature Extraction

II. B. 1) Image Smoothing

In order to reduce the interference of the target image's own organized texture on the pattern information processing, the relative total variation (RTV) model algorithm is applied in order to achieve the purpose of extracting texture smoothing, which aims at smoothing the texture in the image while preserving the salient structures. The relative total variation formula at any point p in the image is as follows:

$$\sum_p \frac{\Phi_x(p)}{\Psi_x(p)+\varepsilon} + \frac{\Phi_y(p)}{\Psi_y(p)+\varepsilon} \tag{7}$$

where ε is a fixed constant, $\varepsilon > 0$, the main role is to ensure that the denominator is not 0, to avoid calculation errors. The window full and intrinsic variants of any point p in the x, y direction in the image are:

$$D_x(f_p) = \sum_{q \in R(p)} h_{p,q} \cdot \left|(\partial_x f)_q\right| \tag{8}$$

$$D_y(f_p) = \sum_{q \in R(p)} h_{p,q} \cdot \left|(\partial_y f)_q\right| \tag{9}$$

$$L_x(f_p) = \left|\sum_{q \in R(p)} h_{p,q} \cdot (\partial_x f)_q\right| \tag{10}$$

$$L_y(f_p) = \left|\sum_{q \in R(p)} h_{p,q} \cdot (\partial_y f)_q\right| \tag{11}$$

where R_p is a rectangular region centered at p, q is any point in the variational region R_p, x, y are the partial differentials of the pixel point q in the x and y directions, respectively, and $h_{p,q}$ is a weight function defined according to the space:

$$h_{p,q} \propto \frac{\exp\left(-\left(\left(x_p - x_q\right)^2 + \left(y_p - y_q\right)^2\right)\right)}{2\sigma^2} \tag{12}$$

p_x and p_y denote the horizontal and vertical coordinates of point p, respectively, and σ controls the window spatial scale.

The RTV algorithm is modeled as:

$$\arg\min_{f} \sum_{p} \left[(f_p - S_p)^2 + \lambda \cdot RTV(f_p) \right] \tag{13}$$

In the above equation: S denotes the input pattern, f denotes the image after the structure is extracted, and λ is a fixed regularization parameter, i.e., the smoothing degree coefficient.

From the above model, it can be seen that the degree of smoothing of the image by the relative full-variate algorithm depends mainly on two parameters, the smoothing degree coefficient λ, and the spatial scale parameter σ.

The smoothing degree coefficient λ is generally taken between 0.01 and 0.05, adjusting λ alone will not make the texture and noise effectively separated, and only increasing λ may cause the image to be blurred and retain the unwanted texture, so it needs to be adjusted at the same time with the spatial scale parameter σ. The value of spatial scale parameter σ is generally between 0 and 5, σ mainly regulates the spatial scale of the window, the value is determined by the size of the noise or dirt in the image, increasing σ can be a good way to remove noise interference and image dirt.

II. B. 2) Image Segmentation Processing

GrabCut is an interactive image segmentation algorithm based on the graph cut implementation that requires the user to manually label the region to be segmented with a rectangle. In the outer image of the rectangle, it is defined as the background, while inside the rectangle, pixels are considered as possible background and foreground. The target image pattern pattern to pattern and pattern to organization is not well connected and selective local segmentation of the target image is performed by GrabCut algorithm.

The steps of GrabCut algorithm are as follows:

(1) One or more rectangles T containing the target are defined in the image, with the outer region of the rectangle as the background region T_B, the inner region of the rectangle as the foreground region $T_F = \varnothing$, and $T_U = T_B$;

(2) Initialize the label $\alpha_n = 0$ for any pixel n in T_B as a background pixel, and initialize the label $\alpha_n = 1$ for each pixel n in T_U as a "possible target" pixel;

(3) Cluster the foreground region T_F and background region T_B into K classes by k-means clustering algorithm to obtain K Gaussian models in GMM;

(4) Model the background and foreground by Gaussian mixture model (GMM) to obtain the initial values (π, μ, σ) of the two GMM parameters θ, where π is the weights, μ is the mean vector, and the covariance matrix σ;

(5) Calculate the GMM component of each pixel within the foreground T_U, i.e., the RGB value of the target pixel n is brought to each Gaussian component in the target GMM, and the one with the highest probability is the one most likely to generate n, i.e., the k_nth Gaussian component of pixel n:

$$k_n := \arg\min_{k_n} D_n(\alpha_n, k_n, \theta, z_n) \tag{14}$$

(6) For a given image data Z, training learning of GMM parameters is performed.

$$\underline{\theta} := \arg\min_{\underline{\theta}} U(\underline{\alpha}, k, \underline{\theta}, z) \tag{15}$$

(7) Segmentation is performed by a maximum-minimum flow algorithm to obtain the minimum energy.

$$\min_{\{\alpha_n, n\in T_U\}} \min_k E(\underline{\alpha}, k, \underline{\theta}, z) \tag{16}$$

(8) Repeat (4) to (7) to optimize the GMM model and segmentation results until the energy E reaches a state of convergence, thus outputting a high quality image.

II. C.Application of digital printing in the field of packaging

In personalized packaging customization, digital printing technology plays its unique advantages. The flexibility of digital printing technology enables packaging designers to achieve diverse and personalized packaging design. For example, in tea packaging, product-related introductions can be flexibly added, including brand stories, product ingredients and information on how to brew, to better attract consumers' attention. Variable data can be printed on labels or packaging, such as variable QR codes to enable consumers and supply chain partners to verify product authenticity and protect high-end consumer goods from counterfeiting. In art packaging, it can greatly enhance the high recognition and sales conversion ability of the product, maximize the uniqueness and personalization of the artwork, and make customers fall in love with a piece of artwork from the beginning of packaging printing.

Digital printing technology can realize the perfect combination of text and pictures, and designers can freely adjust the ratio of graphic and text, and design a different pattern or color scheme for each packaging product, so as to improve the aesthetics of the product and increase the selling point. Through high-precision printing equipment and rich color expressiveness, digital printing is able to achieve high-quality graphic output on a variety of packaging materials to meet the aesthetic needs of consumers for personalized packaging. At the same time, the flexibility and rapid response capability of digital printing also makes the customization of personalized packaging more convenient and efficient. Whether it is a small trial run or a large production run, digital printing can provide solutions to meet the needs.

III. Analysis of the application of personalized packaging technology driven by computer and digital printing technology

III. A. Performance testing

The experiment uses Nikon D850 DSLR camera (sampling frequency 1 frame/s) to collect target images, and the test samples cover five categories of personalized packaging design scenarios such as tea, artwork, etc., and each category contains 10 groups of samples with different lighting conditions and shooting angles. The image processing algorithm is implemented based on the Python OpenCV framework, and the mean clustering (k=5) is used for the clustering analysis of consumer preference data, and the optimal combination of parameters is optimized by the grid search method. The information transmission error test relies on the industrial IoT platform and uses the MQTT protocol to transmit consumer positioning data, with 50 seconds as the observation cycle. The airtightness pass rate test is completed using TS-300 airtightness tester, and the experimental sample covers 20,000 pieces of finished packaging products.

III. A. 1) Image processing

In order to test the processing performance of this paper's image feature extraction algorithm on the captured target image, the root mean square error Y (the sum of the root mean square values of the distances between the target image segmentation results and the initial image pixels) is used as an index to judge the target image processing performance, and there is an inverse proportionality relationship between the Y value and the target image processing performance, i.e., the larger the Y value is, the poorer the target image processing performance is. Conversely, the smaller the Y value, the better the target image processing performance. Set the camera image acquisition frequency as 1 frame/s, randomly select 50 consecutive frames of the target image for image processing, calculate the Y value of each frame after image processing, the Y value of the target image processing results are shown in Figure 1. It can be seen that after the algorithm in this paper processes 50 frames of target images, the Y value of the target image reaches a maximum of about 1.35, in which most of the target image processing results in a Y value below 1.0. The average value of Y value of all target images after processing is 0.957. The above data results fully demonstrate that the algorithm proposed in this paper is more effective for target image processing.

III. A. 2) Information transmission errors

After the implementation of the corresponding processing of the target image can be obtained after the target shape, position and speed and other information, but there is usually a certain deviation in the process of information transmission, the deviation is too large will lead to a decline in the accuracy of the information. The 50s time period is selected to be analyzed, and the information transmission deviation results are shown in Fig. 2. It can be seen that the information deviation is always controlled within 5μrad, which proves that the reliability of information transmission is high.

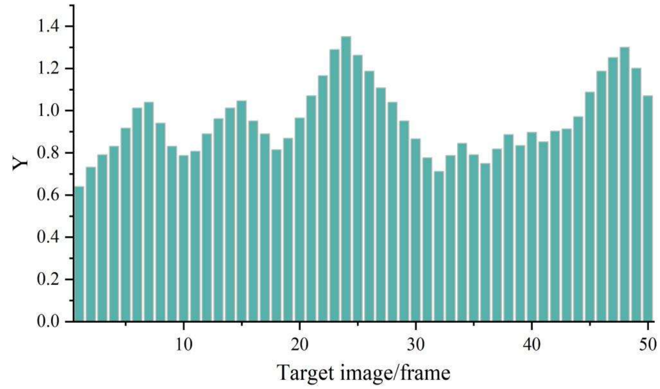

Figure 1: Root mean square error of target image processing results

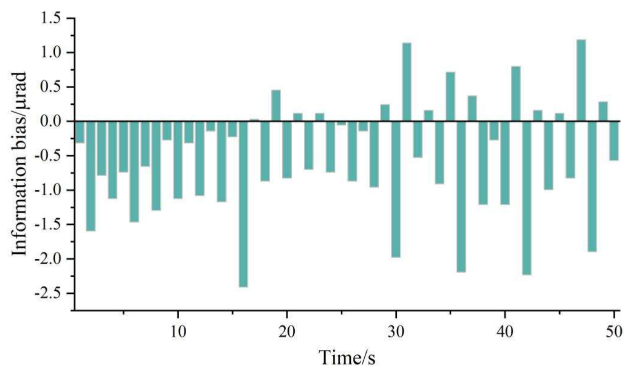

Figure 2: Results of information transmission bias

III. A. 3) Gas-tightness compliance

The airtightness pass rate is one of the important factors affecting the sales of products as well as the profitability and development of enterprises. The lower the airtightness qualification rate, the more product quality can not be guaranteed, the decline in corporate profits, airtightness qualification rate testing process: the packaging is completed after the product is immersed in water, holding pressure for 20s, remove the packaging seal if there is no leakage or bubbles indicating that the packaging airtightness qualified. PLC-based packaging program and embedded technology-based packaging program were set as a control group 1, control group 2, under different programs for 20000 copies of the product packaging airtight compliance rate comparison results shown in Table 1. It can be seen that the average airtightness pass rate of this paper's program reaches 99.987%, and the airtightness pass rate of the control group is 99.494% and 99.123%, respectively, compared with this paper's program is reduced by more than 0.4%, which indicates that the product quality is higher under this paper's program.

Table 1: Comparison results of airtight qualified rate(%)

Test/sample	The proposed	Control group 1	Control group 2
2000	99.98	99.82	99.03
4000	99.96	99.36	99.01
6000	99.97	99.25	99.18
8000	100	99.33	99.14
10000	99.99	99.48	99.09
12000	100	99.56	99.17
14000	100	99.77	99.21
16000	99.99	99.75	99.16
18000	100	99.28	99.09
20000	99.98	99.34	99.15

III. B. Satisfaction with user requirements

In order to verify the applicability of the digital printing and image fusion technology proposed in this paper in the real market environment, the study selected three types of industry head enterprises of tea, high-end liquor and cultural and creative products to carry out a six-month field application practice. The application scenarios cover online e-commerce platforms, offline brick-and-mortar stores and cross-border trade, with a cumulative total of 128,000 pieces of personalized packaging production and over 85,000 consumer services.

In order to quantify the user's acceptance of the technical solution, this paper determines that the user demand of product packaging is divided into five dimensions: use demand, economic demand, social demand, emotional demand and experience demand, and the secondary demand indicators include functional scope, easy to carry, simple operation, reasonable price, brand traceability, packaging moderation, aesthetic characteristics, social media, brand value, value identity, local characteristics, emotional resonance, use interest, and intelligent interaction, a total of 14. A total of 30 questions were created in the mode of positive and negative two-way questions and answers, and five evaluation options were set for participants to choose from: "I like it very much", "I should take it for granted", "I don't care", "I accept it reluctantly" and "I dislike it". A total of 5,000 questionnaires were distributed, of which 3,000 were distributed online and 2,000 were distributed offline, and a total of 4,760 valid questionnaires were collected, with a questionnaire pass rate of 95.2%. The user demand indicators were collected and summarized for the relevant weight calculation, and the KANO model evaluation table was used for comparison, and finally the 14 demand elements were classified with the evaluation index with the highest weight, and the data were normalized at the same time.

Since the traditional KANO scale cannot rank the importance of different demand indicators within the same demand type. Therefore, in order to solve the above problem, the $B_{better}-W_{worse}$ index is introduced to optimize the KANO model and subdivide the importance degree of demand indicators.

The detailed formulas of $B_{better}-W_{worse}$ index are shown in (17)-(18), and the importance degree of the requirements is determined by calculating the user satisfaction coefficient of each requirement indicator.

$$B_{better}/S_{SI}=(A+O)/(A+O+M+I) \tag{17}$$

$$W_{worse}/D_{DSI}=-(M+O)/(A+O+M+I) \tag{18}$$

The B_{better} value "S_{SI}" and the W_{worse} value "D_{DSI}" of each demand indicator are calculated sequentially by the above formula, and user satisfaction "S" is then derived by calculating the distance from the coordinates $(|D_{DSI}|, S_{SI})$ consisting of W_{worse} and B_{better} values to the origin, with the formula as in (19):

$$S=\sqrt{B_{better}^2+W_{worse}^2} \tag{19}$$

After all the demand coordinates are calculated and the demand coordinate system is drawn, the results of the distribution of user satisfaction are shown in Figure 3, with the average value of the two indices as the intersection of vertical and horizontal coordinates, and this is the demarcation line, the coordinate axis is divided into four quadrants, of which the first quadrant is the expected demand attribute (O); the second quadrant is the attractive demand attribute (A); the third quadrant is the undifferentiated demand attribute (I); the fourth quadrant is the basic demand attribute (M). After filling in the coordinates, it can be found that the optimization of the $B_{better}-W_{worse}$ indices makes the allocation of demand types more objective and accurate, and the final ranking table of demand importance is shown in Table 2. Combined with Figure 3 and Table 2, it can be seen that users are most satisfied with the local characteristics of product packaging and least satisfied with the ease of carrying. Among the top five requirements in the satisfaction ranking, three of the desired requirement attributes are accounted for, and the basic requirement attributes, except for the local characteristics, have a lower satisfaction ranking. It shows that the personalized packaging design using the scheme of this paper can well meet the users' desired needs, but the satisfaction of the basic demand attributes still needs to be optimized.

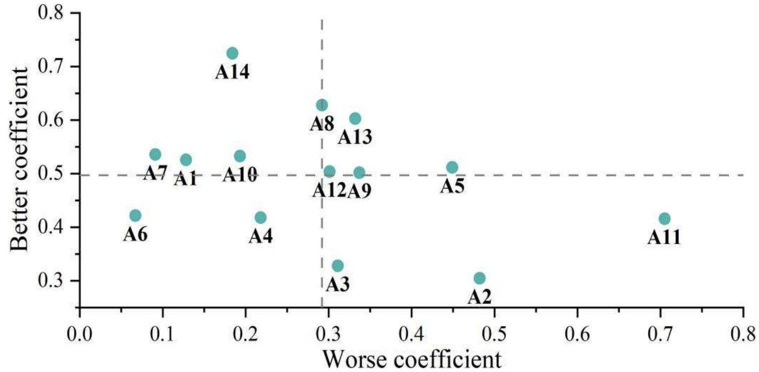

Figure 3: Distribution results of user satisfaction

Table 2: Ranking of requirement importance

Number	Demand indicator	Demand type	Better coefficient	Worse coefficient	S	New demand type	Satisfaction
A1	Functional scope	A	0.526	-0.128	0.562	A	8
A2	Easy to carry	I	0.305	-0.482	0.287	M	14
A3	Simple operation	I	0.328	-0.311	0.418	M	12
A4	Reasonable price	I	0.418	-0.218	0.501	I	11
A5	Brand traceability	A	0.512	-0.449	0.668	O	3
A6	Moderate packaging	I	0.422	-0.067	0.409	I	13
A7	Aesthetic characteristics	A	0.536	-0.091	0.611	A	6
A8	Social media	A	0.628	-0.292	0.573	O	7
A9	Brand value	A	0.502	-0.337	0.527	O	9
A10	Value recognition	I	0.533	-0.193	0.517	A	10
A11	Local characteristics	M	0.416	-0.705	0.802	M	1
A12	Emotional resonance	I	0.504	-0.301	0.613	O	5
A13	Use fun	O	0.603	-0.332	0.637	O	4
A14	Intelligent interaction	A	0.725	-0.184	0.738	A	2

IV. Conclusion

In this paper, we design a personalized packaging scheme with digital printing technology and computer image fusion, and verify the practical application effect of the scheme with experiments and practice.

In this paper, the image processing algorithm processes 50 frames of target images, and the Y value of the target image reaches a maximum of about 1.35, of which most of the target image processing results in a Y value of less than 1.0. The average value of Y value of all target images after processing is 0.957, and the information deviation is always controlled within 5 μrad. The average airtightness pass rate of this paper's scheme reaches 99.987%, and the airtightness pass rates of the control group are 99.494% and 99.123%, respectively, which are reduced by more than 0.4% compared with this paper's scheme, indicating that the quality of products under this paper's scheme is higher.

User demand satisfaction survey shows that the top five demands in the satisfaction ranking of the desired demand attributes accounted for three, the basic demand attributes in addition to the local characteristics of the satisfaction ranking are lower. It shows that the personalized packaging design using this paper's scheme can satisfy the user's desired needs well, but the satisfaction of the basic demand attributes still needs to be optimized.

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