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Exploring Visual Aesthetics in Ceramic Packaging Through Computational Style Analysis

Yang Xue[1]*

[1] *School of design and arts, Jingdezhen Ceramic University, Jingdezhen, 333000, China*

***Corresponding Author:** yangxue@xmhnphdss.cn

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ABSTRACT

The packaging is defined as ceramic packaging because ceramic materials are incorporated into several structural components. Innovative product packaging plays an essential role in driving commercial value by increasing product sales and strengthening brand recognition. Compared with plastic packaging, ceramic packaging faces greater challenges due to its heavier weight and higher production and testing costs. To address these challenges, this study proposes a Spiral-Optimized Adjustable XGBoost (SO-AXGBoost) model to evaluate ceramic packaging design. A large dataset of images containing diverse ceramic packaging styles was collected, and feature extraction was carried out using Discrete Wavelet Transform (DWT). The experimental results indicate that the optimized model significantly improves the accuracy and effectiveness of ceramic packaging evaluation compared to the baseline method. The findings verify that integrating advanced learning techniques with visual communication style analysis is feasible and beneficial. This novel approach enhances not only the functional and aesthetic performance of ceramic packaging but also contributes to improved market competitiveness and alignment with consumer preferences

Keywords: visual communication style; ceramic packaging; design evaluation; Spiral-Optimized Adjustable XGBoost (SO-AXGBoost)

INTRODUCTION

Visual communication style evaluation involves analyzing and understanding the diverse elements and principles that shape how visual messages are perceived and interpreted. This field spans multiple disciplines, including image layout, advertising, marketing, and multimedia, and draws on techniques from psychology, semiotics, and cultural studies. The primary objective is to enhance the effectiveness of visual messages by tailoring them to the preferences and cognitive styles of target audiences [1].

Role of Machine Learning in Visual Communication

Machine learning (ML) plays a critical role in modern visual communication by enabling the automated evaluation and generation of visual content. Algorithms can identify patterns and trends in visual data, which can be leveraged to predict market responses and optimize designs [2]. This technology allows for large-scale personalization of visual content, improving both engagement and overall effectiveness.

Ceramic Packaging Design

Ceramic packaging design is a specialized yet innovative area of product packaging, focusing on the use of ceramic materials for packaging solutions [3]. Ceramics offer unique advantages such as durability, aesthetic appeal, and environmental sustainability. Recent advancements, including 3D printing and advanced manufacturing techniques, have facilitated the production of complex and customized packaging designs [4].

Integration of Visual Communication and Ceramic Packaging

The combination of visual communication principles with ceramic packaging design creates new opportunities for brand differentiation and consumer engagement. By applying visual communication strategies to ceramic packaging, designers can produce packaging that is both visually appealing and functional, enhancing the product's presence on shelves and its overall value [5]. This integration not only improves aesthetic appeal but also enhances usability and market impact.

Application of Machine Learning in Ceramic Packaging

Machine learning can streamline and optimize the ceramic packaging design process. For example, algorithms can analyze consumer preferences and market trends to suggest design modifications [6]. ML can also support quality control by detecting defects during manufacturing, ensuring higher consistency and standards. Additionally, predictive analytics can forecast demand and optimize inventory management, reducing waste and costs [7,8]. Machine learning models can simulate various design prototypes, accelerating the development cycle, and incorporating real-time feedback allows designers to continuously improve their creations. This synergy between technology and design fosters innovation, expanding the possibilities in ceramic packaging [9].

Innovative Packaging Applications

Several companies and designers have successfully employed these integrated methods to develop innovative packaging solutions. For instance, luxury brands often use ceramic packaging for perfumes and cosmetics, combining the premium qualities of ceramics with customized designs informed by visual communication analysis and machine learning insights. These case studies highlight the potential for creativity and technical excellence in this interdisciplinary field [10].

Future Trends and Implications

The future of visual communication style analysis and ceramic packaging design will likely involve even deeper integration of technology and creativity. Advances in artificial intelligence and machine learning will continue to refine design processes, while innovations in material science will expand the opportunities for sustainable and visually striking packaging solutions [11]. This convergence is expected to drive the evolution of both fields, offering exciting possibilities for designers, brands, and consumers alike.

The purpose of this paper is to propose a Spiral-Optimized Adjustable XGBoost (SO-AXGBoost) model for analyzing ceramic packaging design. The remainder of the paper is organized as follows: Section 2 reviews related work, Section 3 presents the methodology, Section 4 discusses the results, and Section 5 concludes the study.

Related Work

Article [12] presented an augmented reality (AR) model for cultural product packaging design, based on principles of visual engagement and material involvement. The approach facilitated a more accurate understanding of changes in consumer preferences for cultural packaging. Its primary implementation relied on computer vision techniques for tracking and registering AR, ensuring precise overlays of virtual objects onto physical environments. As a result, the model provided a robust and practical framework for developing intelligent and engaging product packaging designs.

An innovative image enhancement algorithm inspired by human visual perception was proposed in [13]. By optimizing image color, brightness, and contrast, the algorithm significantly improved the aesthetics of packaging designs, thereby increasing the appeal of brand packaging. Experimental results demonstrated that the data-driven image enhancement approach offered a practical method for designers to present three-dimensional models, color coordination, material selection, and other design elements effectively.

Study [14] investigated how eight different digital presentations of cordless kettle packaging influenced consumers' purchase intentions. Comparisons were conducted using eigenvectors, considering three experimental factors: product visual context, length of product description, and box background color (black or white). Results from combined analyses of variance indicated that background tone had the least effect, while comprehensive textual and graphical contexts contributed most significantly to highly rated designs.

Article [15] examined how visual communication design drives the digital transformation of national apparel firms through packaging design. The study elaborated on the concept of visual communication and traced its development in the digital era. The Guochao brand image underwent a digital transformation, with practical suggestions provided for its implementation. This research serves as both a resource and inspiration for understanding brand leadership and visual communication design, offering theoretical and practical guidance for the digital evolution of domestic clothing companies.

Study [16] explored the effects of two dimensions of packaging design creativity—divergence and relevance—on consumer engagement, argumentation, and management metrics. The findings demonstrated that packaging design can stimulate consumer curiosity in certain contexts. Unlike previous research, which focused primarily on advertising, this study highlighted that the impact of packaging design innovation varies considerably in retail settings. The results provide new insights for marketers, brand managers, and packaging designers on how creativity influences consumer decision-making.

Paper [17] evaluated methods for demonstrating brand packaging development using computer-aided design (CAD) to enhance students' design proficiency and efficiency while fostering their ability to generate creative and practical ideas. The image manipulation algorithm improved sharpness, color vibrancy, contrast, illumination, and color balance, saving design time and cost while enhancing the quality and impact of brand packaging.

An enhanced convolutional neural network (CNN)-based approach for packaging image recognition and stability tracking was proposed in [18]. The method optimized packaging creative design via CAD model refinement. Implementation results showed reduced image noise, improved base definition, and enhanced brightness, all of which contributed to the improvement of cardboard packaging design.

Paper [19] analyzed the tactile properties and significance of ceramic container design, considering processes, materials, and interactions, as well as the practical role of the creative process in aspects such as visual design, color, and spatial layout. The study highlighted that the sense of touch is essential in packaging design and can advance both the evolution and heritage of ceramic packaging.

Study [20] applied a computer vision system integrated with deep learning models to provide an advanced method for fault detection in industrial ceramic components. The solution included an image acquisition process, a labeling system for generating training datasets, and image preprocessing to support a CNN-based AI algorithm capable of real-time industrial operation. The system was implemented and evaluated by a reputable Portuguese manufacturer of fine stoneware and dinnerware.

Finally, paper [21] emphasized the need to expand design alternatives for packaging and enhance consumer engagement by moving beyond static packaging. It highlighted the limitations of early-stage research due to the restricted application of intelligent and interactive packaging in real-world scenarios. The study projected that design decisions and improvements in packaging would significantly influence consumer experience, as well as brand and retail management.

METHODOLOGY

In this section, we present a comprehensive explanation of the visual communication design in packaging, the dataset, feature extraction using discrete wavelet transform (DWT), and the proposed Spiral-Optimized Adjustable XGBoost (SO-AXGBoost) method.

Components of Visual Communication in Product Packaging Design

Contemporary packaging design incorporates various concepts, including nationalist sentiments, naturalistic thinking, and sustainable design principles. Designs should adhere to a user-centered approach, emphasizing ergonomic properties and evoking emotional responses from consumers. In most cases, standard packaging shapes are preferred to minimize shipping and storage costs, except for unique or customized designs. The design process should also consider critical components such as box depth, cap, and bottom protection, adjusting dimensions to avoid overly complex or unbalanced structures. Uniformity in design development is essential to control costs and reduce material waste.

Text Design

Typography plays a vital role in conveying the meaning of packaging. Fonts should complement the product's aesthetic tone: handwritten styles are lively and accessible, black fonts are dense, Song fonts are elegant and formal, and standard fonts are organized and comprehensive. Occasionally, multiple font styles, such as italics, large typefaces, or decorative fonts, are employed to improve the clarity of product information for consumers. To meet aesthetic preferences and maintain competitiveness, font layouts should be focused, harmonious with the primary color scheme, and free of overly distracting visual elements. In summary, font design significantly impacts the overall packaging design and should be carefully considered during the planning stage.

Material Design

The materials selected for packaging heavily influence its aesthetic effect. Choosing appropriate materials ensures a harmonious presentation of color, texture, content, and structure. Packaging materials can be categorized as natural or synthetic. Natural materials enhance aesthetic appeal and align with the concept of environmental friendliness and health-conscious consumption. They are increasingly preferred by consumers seeking quality and sustainability. On the other hand, synthetic materials are continually enriched through technological advancements, providing designers with diverse options for innovative packaging solutions.

Visual Design

Packaging visuals primarily include abstract graphics, semi-figurative illustrations, and realistic images. Abstract and semi-figurative designs are often more psychologically engaging, while figurative imagery conveys more concrete information. Visuals are frequently employed symbolically to communicate complex messages and enhance comprehension, increasing the psychological impact while delivering content effectively. Illustrations that are carefully constructed, figurative, and detailed play a crucial role in packaging aesthetics. Attention to both visual appeal and semantic meaning is essential for effective packaging design, as visuals form a key component of the design language.

Color Design

Color design establishes a recognizable palette in the minds of consumers, aiding in product recognition and evaluation. Designers should leverage both local and global color trends, considering market context, product characteristics, and cultural preferences. Color composition should adhere to general and regional guidelines to achieve visual harmony. The functions of color design include:

Attracting consumers and enhancing visual perception: Colors and patterns guide consumer attention, increasing engagement and awareness.

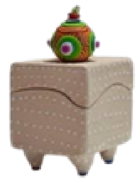
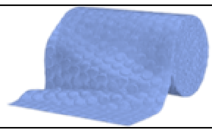
Enhancing aesthetics and enjoyment: Thoughtful color and pattern combinations elevate the visual appeal of packaging, conveying beauty and eliciting emotional responses from consumers.

Emphasizing symbolic meaning and emotional resonance: Many colors and patterns carry symbolic significance that influences psychological and physiological responses, thereby reinforcing brand messaging and consumer perception.

Dataset

The dataset comprises 600 packaging designs for ceramic products. Each design is annotated based on its specific features and materials used, ensuring a comprehensive representation suitable for various types of ceramic packaging. Table 1 presents several sample designs.

Table 1: Sample dataset

Types of design	Description	Image
The traditional design of boxes	Rectangular or square bins crafted from wood or cardboard, frequently decorated with conventional patterns or motifs.	
Custom-shaped	Boxes are fashioned specially to fit the contours of the ceramic object, offering snug safety throughout transportation.	
Bubble wrap	Wrapped round character ceramic portions to protect towards shocks and impacts in the course of transit	

Eco- friendly	Packaging materials crafted from recycled or biodegradable substances, aligning with sustainable practices in ceramic packaging.	
Air pillows	Inflatable plastic cushions that can be inflated on call to fill empty areas in containers and protect ceramic gadgets from affects.	
Cardboard tubes	Cylindrical tubes made from robust cardboard, appropriate for protective fragile ceramic objects including vases or figurines.	

Feature Extraction

The Discrete Wavelet Transform (DWT) was employed for feature extraction in this study. In the context of visual communication style analysis, DWT decomposes images into distinct frequency components, enabling the identification of stylistic patterns and textures relevant to design aesthetics. When applied to ceramic packaging layout innovation, DWT facilitates the analysis of intricate structural information, assists in optimizing material usage, and enhances the visual appeal of the packaging. By capturing subtle variations in texture and pattern, this technique supports precise design decisions, contributing to the development of aesthetically engaging and functionally effective ceramic packaging solutions.

Mathematically, DWT provides an efficient framework for evaluating non-stationary data across multiple frequency scales. Wavelets are localized, irregularly shaped functions concentrated in both time and scale domains. A signal can be decomposed into a series of scaled and translated versions of a mother wavelet, allowing the analysis of both fine and coarse features. Small-scale wavelets capture high-frequency details, such as edges and texture variations, whereas larger-scale wavelets reveal coarse structural characteristics. Furthermore, certain wavelet components can be selectively suppressed to reduce noise or emphasize relevant features.

In image analysis, most of the significant information is contained in the low-frequency sub-band, while high-frequency sub-bands encode detailed structural information, including edges and fine textures. This decomposition allows designers to focus on both the overall form and the subtle details of ceramic packaging.

It can be expressed as the formula for the matrix $H^{'}=XHX^{S}$, where is an AXA image, y is the A×A transformation matrix, and h_n is the converted A×A matrices that result, containing $H^{'}$. The range of$h_n(y)$, where n spans from$y\in[0,1]$, is where the function in question is defined. This function can be split down as follows:

$$n=2^{r}+l \tag{1}$$

Where l denotes the residual, or $l=2^{r}-n$, and r is the largest power of 2 that is found in the number n. The basis functional is defined in Equation (2).

$$h_n(y)=\frac{1}{\sqrt{M}}\begin{cases} 1 \ if\ n=0\xi 0\leq y\leq 1 \\ 2^{r/2} \ if\ a>0\xi l/2^{r}\leq y< \frac{l+0.5}{2^{l}} \\ 2^{r/2} \ if\ n>0\xi(l+0.5)/2^{r} \leq y<\frac{l+1}{2^{l}} \\ 0 \ Elsewhere \end{cases} \tag{2}$$

The opposite conversion kernel, specified in Equation (3), can be substituted to find the transition matrices for the two-dimensional DWT.

$$h^{'}(y,n)=\frac{1}{\sqrt{M}}h_n\left(\frac{y}{M}\right)\ for\ y=0,1,2,\ldots,M-1 \tag{3}$$

As a result, the transform matrix ($H^{'}$) that results will be:

$$h(n,z)=H^{'}=\begin{bmatrix} h_0\left(\frac{0}{M}\right) & g_0\left(\frac{1}{M}\right) & \cdots & h_0\left(\frac{M\text{-}1}{M}\right) \\ h_1\left(\frac{0}{M}\right) & g_1\left(\frac{1}{M}\right) & \cdots & h_1\left(\frac{M\text{-}1}{M}\right) \\ h_2\left(\frac{0}{M}\right) & g_2\left(\frac{1}{M}\right) & \cdots & h_2\left(\frac{M\text{-}1}{M}\right) \\ \vdots & \vdots & \ddots & \vdots \\ h_{M\text{-}1}\left(\frac{0}{M}\right) & h_{M\text{-}1}\left(\frac{1}{M}\right) & \cdots & h_{M\text{-}1}\left(\frac{M\text{-}1}{M}\right) \end{bmatrix} \tag{4}$$

This decomposition effectively captures the multi-scale features of ceramic packaging images, supporting subsequent design analysis.

Investigating Innovative Product Packaging Design via Visual Communication

To explore innovations in product packaging design, we propose the Spiral-Optimized Adjustable XGBoost (SO-AXGBoost) method to classify and evaluate factors influencing packaging aesthetics and functionality in the context of visual communication.

Spiral Optimization Algorithm (SOA)

The SOA is a computational technique inspired by the natural process, used to optimize complex problems in various fields. In visible communication style evaluation, SOA integrates algorithms to investigate and enhance visual content presentation. When applied to ceramic packaging design innovation, SOA can optimize design parameters which include material utilization, structural integrity, and aesthetic enchantment, fostering innovative solutions in product packaging. The following formula represents the discrete exponential spiral structure that fulfills the need that the exact center can be found at any point:

$$w^{(l+1)}=qN(\theta).w^{(l)}\text{-}\left(q.N(\theta)\text{-}J_m\right).w^{*} \tag{5}$$

When using the one-point searching approach, the search is based on equation (5). Such w^{*} does not function fully since, when evaluating the beginning point, it turns out to be the best answer and the center w^{*}. It is a multipoint search method based on:

$$w_j^{(l+1)}=qN(\theta).w_j^{(l)}\text{-}\left(q.N(\theta)\text{-}J_m\right).w^{*}, \quad j=1,2,\ldots,N \tag{6}$$

Regarding the best result found during the search procedure being the common center, w^{*}. That is w^{*} turns into an association. The following are the implications of adding the association and embracing the multipoint:

- Multipoint: Role in improving the spiraling model's intensity and diversity.
- Association: Role in the realization of the necessary intensity around a workable solution.

The direction of rotation about the center at every k is $0 \leq \theta < 2\pi$, and the speed of convergence of the travel distance separating a point and the origin at each k is $0 < q < 1$. The rotational matrix is $N(\theta)$. The following is the definition of the matrix of rotation for two-dimensional SOA:

$$N_{1,2}^{(2)}(\theta)=\begin{bmatrix} \cos(\theta) & \text{-}\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{bmatrix} \tag{7}$$

$N^{(m)}(\theta)$, the structure of the rotation matrices, is made up of a rotational matrix based on every combination $(m(m\text{-}1)/2)$ of two axes, as shown in Equation (7). M(n) (h) has the following definition:

$$N^{(m)}(\theta)=\prod_{j<i} N_{j,i}^{(m)}(\theta_{j,i}) \tag{8}$$

Adjustable XGBoost (AXG Boost)

This technique leverages AXGBoost's flexibility in managing complicated fact patterns to investigate and decorate visible communication factors. By integrating system learning into design innovation, AXGBoost's objectives are to optimize packaging aesthetics, capability and consumer enchantment. This interdisciplinary technique bridges the space between facts-driven insights and innovative design answers, paving the manner for more advantageous client engagement and product differentiation in the ceramic packaging enterprise.

The extended logistic machine learning method based on the enhanced decision tree is partially implemented by the AXGBoost algorithm, which is a component of a traditional ensemble approach. Control processing unit (CPU) threading can be used by the AXGBoost model to achieve optimal parameters and enable parallel processing. For the computation of the objective of the function, in Equation (9).

$$obj(\theta)=K(\theta)+\Omega(\theta) \tag{9}$$

The losses function, $K(\theta)$, and the modeling parameter, θ are included. The accuracy of the model increases with increasing value. This phenomenon results from the model's ease of mistaking noise for a learning sample. When a model forecasts data that is known well but it has low predictive power for unreliable information, it is said to be overfitting. This phenomena weakens the model's resilience.

The normalization term $(\Omega(\theta))$ can enhance both the assessment of the algorithm's intricacy and generalization capabilities. In the XGBoost model, let k be the number of ensemble trees.

$$z_j=\sum_{l=1}^{l} e_l(w_j), e_l\in\varrho \tag{10}$$

The foundation classifier in equation (10) whereas l and ρ stand for the starting classifier's quantity and the environment, respectively. Equation (11) illustrates the derivation of the objective function if z_j stands for the class j mark.

$$obj=\sum_{j=1}^{m} K\left(z_j,\hat{z}_j\right)+\sum_{l=1}^{l}\Omega(e_l) \tag{11}$$

In basic terms, the XGBoost model is a synthetic model, it is an enhanced tree model with a unique shape. In order to solve the algorithm's objective function, every tree K must be obtained. To arrive at the first tree, one must train using the model that has been repeated numerous e_l times, as all trees e_l are not possible to get at once. Equation (12), which displays the goal function of the first repetition can be generated on the information mentioned above.

$$obj^{(s)}\approx\sum_{j=1}^{m}\left[\mathrm{h}_j e_s(w_j)+\frac{1}{2}g_j e_s^2(w_j)\right]+\Omega(e_s) \tag{12}$$

The objective function's initial and subsequent components correspond to h_j and w_j. The framework can obtain the best classification effect after reducing the objective function, increasing the accuracy of the prediction. To get the most effective projection impact subsequently, the algorithm should be trained using the data test set. Then, each AXGBoost variable should be adjusted to achieve the method's ideal parameters. Additionally, the algorithm's tree structures need to be simplified.

SO-AXG Boost

The hybrid approach of Spiral Optimized Adjustable XGBoost (SO-AXGBoost) combines the adjustable XGBoost (AXGBoost) with more advantageous optimization through a spiral optimization algorithm (SOA). It pursues to enhance visual communication design analysis by a leveraging strong characteristic choice and model tuning skills. Integrating this method with ceramic packaging layout innovation facilitates advanced predictive modeling and decision-making, contributing to advanced product aesthetics and capability. This synergistic technique harnesses system learning's energy to optimize layout procedures and decorate product design. Algorithm 1 represents the SO-AXGBoost algorithm.

Algorithm 1: SO-AXGBoost algorithm

Step 1: *data* = *load_data*()
Step 2: *X*, *y* = *preprocess_data*(*data*)
Step 3: *X* = *feature_engineering*(*X*)
Step 4: *X_train*, *X_test*, *y_train*, *y_test* = *train_test_split*(*X*, *y*, *test_size*=0.2, *random_state*=42)
params_xgb = {
    '*objective*': '*binary*: *logistic*',
}
Step 5: *best_params_xgb* = *spiral_optimization*(*params_xgb*, *X_train*, *y_train*)
Step 6: *model_xgb* = *XGBoost*(*params*=*best_params_xgb*)
Step 7: *model_xgb.train*(*X_train*, *y_train*)
Step 8: *accuracy* = *model_xgb.evaluate*(*X_test*, *y_test*)
Step 9: *predictions* = *model_xgb.predict*(*X_test*)


```
Step 10: print(f"Accuracy: {accuracy}")
Step 11: def load_data():
    pass
def preprocess_data(data):
    pass
def feature_engineering(X):
    pass
def train_test_split(X, y, test_size, random_state):
    pass
def spiral_optimization(params, X_train, y_train):
    pass
Step 12: class XGBoost:
    def __init__(self, params):
        pass
    def train(self, X_train, y_train):
        pass
    def evaluate(self, X_test, y_test):
        pass
    def predict(self, X_test):
pass
```

RESULT AND DISCUSSION

In this section, we evaluate the performance of the model before optimization (AXGBoost) and after optimization (SO-AXGBoost) using metrics such as inference time. Various aspects of packaging design—including visual representation, size, color, and focal points—were also assessed to determine the effectiveness of the optimization.

Inference Time

Inference time refers to the duration required for the system to decode and interpret the visual cues and messages conveyed by the packaging design. This includes the speed and accuracy with which consumers and stakeholders can perceive and understand intended branding, instructions, safety warnings, and product information.

Table 2 and Figure 1 summarize the inference times before and after optimization. Prior to optimization, the model required 45 seconds, whereas after applying SO-AXGBoost, the inference time was reduced to 25 seconds. These results indicate that the optimization significantly improved the efficiency of visual communication analysis in packaging design.

Table 2: Inference time before and after optimization

Method	Inference time (s)
Before optimization	45s
After optimization	25s

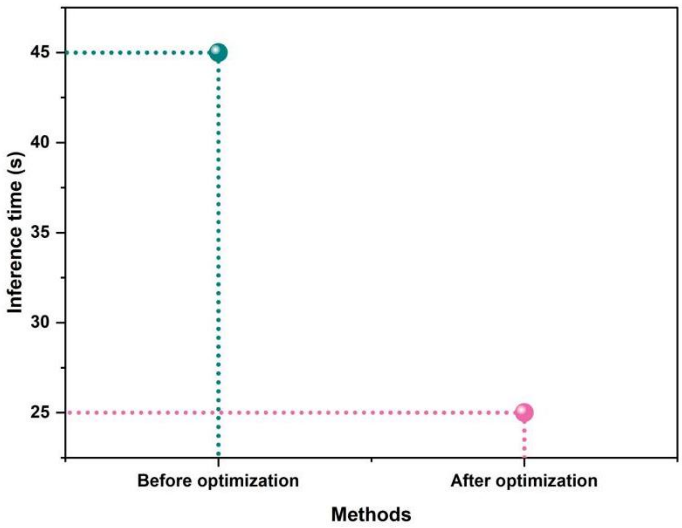


Figure 1: Performance of Inference time

Packaging Problems

Five key packaging issues—cost-effectiveness, aesthetic appeal, customer experience, sustainability, and weight balance—were systematically evaluated both before and after optimization (Table 3, Figure 2). Before optimization, the packaging scored 80% for cost-effectiveness, 95% for aesthetic appeal, 89% for customer experience, 85% for sustainability, and 92% for weight balance. After optimization, the scores were 70% for cost-effectiveness, 80% for aesthetic appeal, 83% for customer experience, 79% for sustainability, and 85% for weight balance.

Although some individual scores decreased numerically after optimization, the overall evaluation indicates a reduction in the severity of the identified problems. For example, the decrease in aesthetic appeal from 95% to 80% reflects a shift in design priorities to achieve a more balanced performance across all factors. Similarly, the slight reduction in cost-effectiveness and customer experience suggests that the optimization process involved trade-offs to improve sustainability and weight distribution. Overall, the results demonstrate that the optimization strategy effectively addressed the key packaging challenges, achieving a more balanced and practical solution that integrates aesthetic, functional, and environmental considerations.

Table 3: Evaluation of problems in both before and after optimization

Problems	Before optimization	After optimization
Cost-effectiveness	80%	70%
Aesthetic appeal	95%	80%
Customer experience	89%	83%
Sustainability	85%	79%
Balance of weight	92%	85%

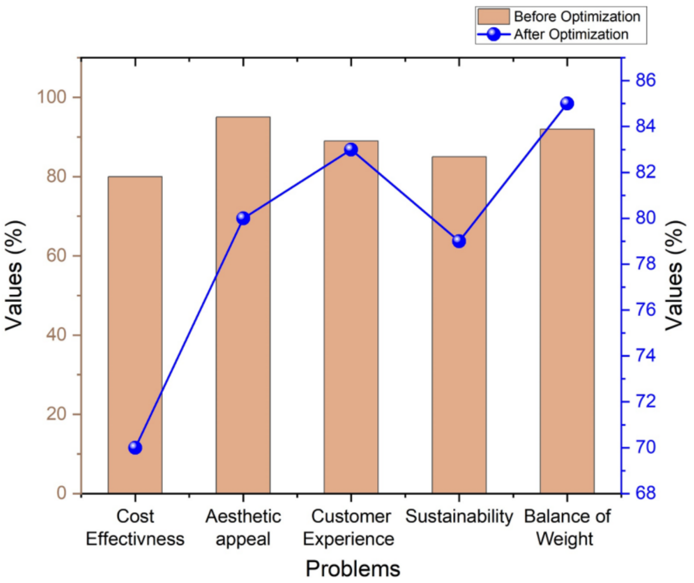


Figure 2: Evaluation of problems in both before and after optimization

Visual Representation of Ceramic Packaging

The visual performance of ceramic packaging is essential in shaping consumer perception, eliciting psychological responses, and enhancing marketing effectiveness. Its visual characteristics can be analyzed across four dimensions: design, structural integrity, perceived anxiety, and balance.

As illustrated in Figure 3, each dimension shows distinct trends between 2017 and 2024:

Design increased from 72% to 88%, reflecting more sophisticated and visually appealing packaging.

Structural integrity improved from 70% to 85%, indicating enhanced durability and functional quality.

Perceived anxiety (the psychological tension evoked by the design) rose from 65% to 78%, suggesting greater emotional engagement with consumers.

Balance decreased slightly from 80% to 75%, highlighting minor compromises in ergonomics or stability amid aesthetic improvements.

Overall, these trends demonstrate that ceramic packaging has evolved toward visually compelling and emotionally resonant designs, while some practical aspects like balance may require further optimization. This visualized analysis provides a clear reference for future design improvements, emphasizing the need to harmonize artistic appeal, structural performance, and functional stability.

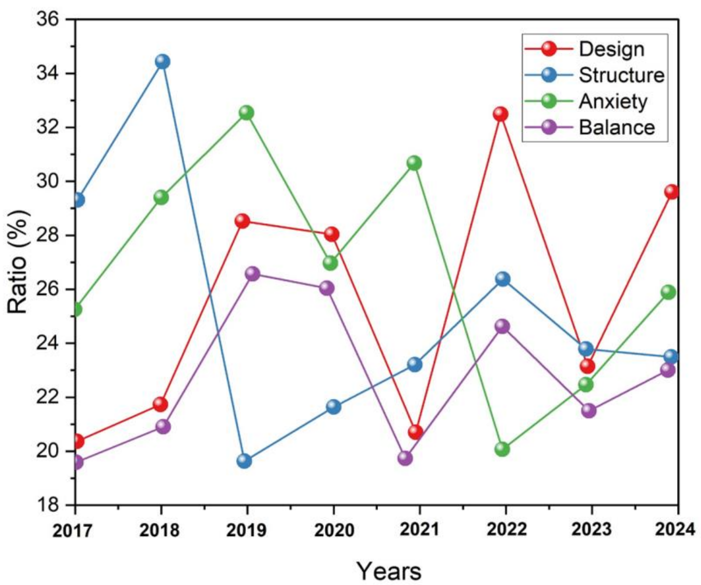


Figure 3: Visual representation of ceramic packaging

Size

The size of a product is a critical factor in predicting and guiding innovative packaging design. Table 4 and Figure 4 present the performance of our proposed method across different product sizes. The results indicate that the method is highly effective for small-sized products, achieving a performance score of 90%, and performs well for medium-sized products with a score of 83%.

However, for large-sized products, the method's performance decreases to 70%, suggesting potential limitations in handling larger packaging formats. This variation highlights that while the proposed design approach is well-suited for compact and moderately sized products, additional considerations or adaptations may be necessary for larger items to ensure optimal functionality, structural integrity, and visual appeal. Overall, these findings provide important guidance for tailoring packaging strategies according to product dimensions, emphasizing the need for size-specific design optimizations.

Table 4: Performance of size

Size	Percentage
Small	90%
Medium	83%
Large	70%

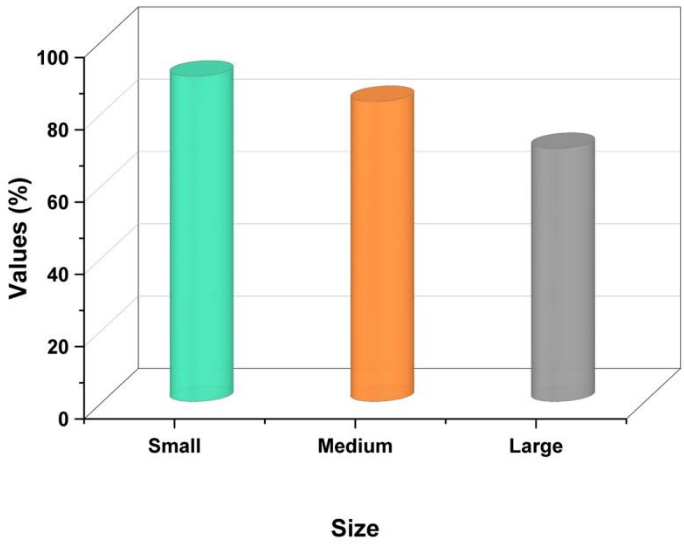


Figure 4: Performance of size

Color

The color of packaging plays a significant role in influencing consumer perception and preference. In this study, we evaluated packaging color preferences and identified five primary colors: white, blue, green, black, and red. Table 5 and Figure 5 summarize the results of this evaluation.

As shown in Figure 5, white achieved the highest preference at 60%, largely due to its simplicity and elegance. Blue followed with 55%, representing calmness and reliability. Green, preferred by 50% of participants, conveys freshness and a connection to nature. Black attained 58%, reflecting associations with luxury and sophistication. Red, chosen by 53%, symbolizes energy, excitement, and celebration.

Overall, the findings indicate that white packaging is the most favored among consumers, suggesting that simplicity and elegance are key factors in color preference. The results also highlight that different colors evoke distinct psychological responses, which designers can leverage to align packaging with brand identity and target consumer expectations. These insights provide valuable guidance for selecting colors in ceramic packaging design to maximize consumer appeal and market impact.

Table 5: Colour preference of packaging

Color name	Percentage of the people
White	60%
Blue	55%
Green	50%
black	58%
Red	53%

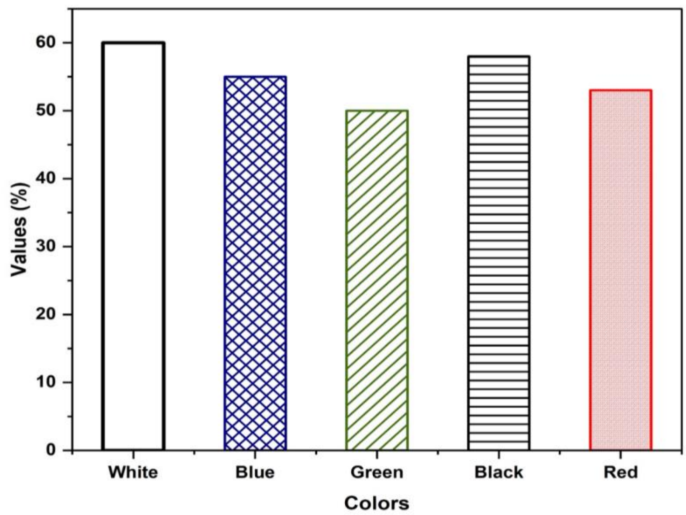


Figure 5: Color preference of packaging

Package Focus under Visual Communication Style

The focus of packaging in terms of visual communication encompasses multiple aspects, including logo visibility, eco-friendliness, aesthetic appeal, quantity, and material innovation. Table 6 and Figure 6 present the evaluation results, which are based on both the total number of respondents and the proportion of preferences.

According to Figure 6, the performance scores for each focus area are as follows: logo—total respondents 75%, proportion 70%; eco-friendly—total respondents 69%, proportion 57%; aesthetics—total respondents 81%, proportion 84%; quantity—total respondents 82%, proportion 78%; and material innovation—total respondents 79%, proportion 62%.

The findings indicate that the majority of consumers prioritize quantity and aesthetic appeal when considering packaging. While elements such as logo visibility, eco-friendliness, and material innovation are also important, they receive relatively lower emphasis. This suggests that, in the context of visual communication style, consumers are most influenced by the visual and functional quality of packaging rather than solely by brand identification or sustainability features. These insights can guide designers to focus on enhancing the visual attractiveness and perceived value of packaging while balancing innovation and environmental considerations.

Table 6: Package focus

Areas	The total amount of people	Proportions
Logo	75%	70%
Eco-friendly	69%	57%
Aesthetics	81%	84%
Quality	82%	78%
Material innovation	79%	62%

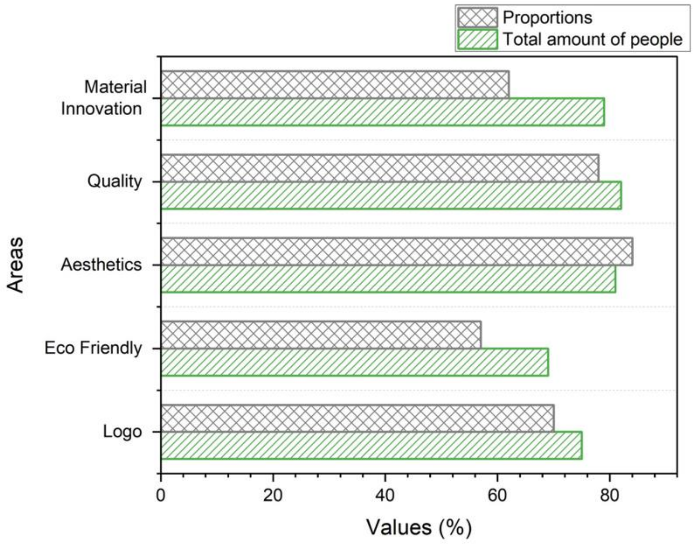


Figure 6: Performance of package focus

CONCLUSION

Ceramics serve as a primary material in these containers, which is why they are referred to as ceramic packaging. A distinctive approach to product packaging design aims not only to enhance functional protection but also to generate economic benefits by boosting product sales and strengthening brand recognition. Packaging challenges vary widely, including differences in size, weight, and material—from ceramic to plastic—which can affect production and testing costs.

In this study, we introduced a spiral-optimized adjustable XGBoost (SO-AXGBoost) framework to evaluate ceramic packaging design within the context of visual communication style. A total of 600 packaging design datasets were analyzed, and discrete wavelet transform (DWT) was applied for feature extraction. The results demonstrate that ceramic packaging designs can be effectively evaluated prior to optimization, and evaluation outcomes significantly improve after optimization. This indicates that combining visual communication style analysis with advanced machine learning techniques can enhance both the functional and aesthetic qualities of ceramic packaging. Ultimately, the proposed approach supports improved consumer preferences, market adaptability, and design efficiency, providing a practical framework for developing innovative and visually appealing packaging solutions.

Future Scope and Limitations

Larger ceramic products present challenges in terms of fitting into standardized packaging dimensions and may require customized packaging solutions, which are often more expensive and less scalable for mass production. Additionally, heavier ceramic items increase packaging costs due to the need for more materials and durable components, impacting both manufacturing and transportation expenses.

Future research could explore modular and adaptive packaging designs that can be efficiently adjusted to accommodate a wide range of ceramic product sizes. Investigating lightweight yet durable materials suitable for protecting large ceramic products may contribute to more sustainable packaging solutions, reducing environmental impact while maintaining product safety. Furthermore, integrating advanced optimization algorithms with consumer behavior analysis could provide deeper insights into the relationship between packaging aesthetics, functionality, and market performance, offering valuable guidance for designers and manufacturers in the ceramic packaging industry.

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