International Journal of Information Technologies and Systems Approach
Volume 17 • Issue 1 • January-December 2024

Design and Evaluation of Packaging Art Based on Sentimental Value Calculation and Clustering

Fang Wu
Chongqing Vocational Institute of Safety Technology, China

Bilal Alatas
https://orcid.org/0000-0002-3513-0329
Firat University, Turkey

ABSTRACT

This paper introduces the cultural dimension of product packaging, elucidates the quantification principle and methodology governing customer aesthetic experiences, propounds an innovative packaging style design approach, and presents an evaluation model based on an enhanced neural network. Using tea packaging design as an illustrative case, the methodology initially aligns adjectives, subsequently computes the emotional depth value, and ultimately derives the corresponding correlation between customer emotional experiences and design elements through a neural network. Subsequently, the designed model is validated using tea packaging design as a practical example. The outcomes demonstrate the model's accuracy and efficacy in establishing the mapping between design elements and aesthetic experiences, offering novel insights for the evolution of packaging design in the contemporary market landscape.

KEYWORDS

Packaging Design, Aesthetic Experience, Emotional Value, Neural Network, Design Element, Modern Market, Quantification Principle, Tea

In the 21st century, global product design has embarked on a new phase of evolution. The emphasis has shifted towards emotional considerations, with heightened demands for emotional engagement. Packaging design, as the culmination of production and the inaugural stage in the commodity circulation process, serves as the conduit for consumers to cognitively interact with products (Zeng et al., 2020; Dell'Era et al., 2020). Packaging design represents a comprehensive discipline spanning two major domains: art design and technical design, seamlessly integrating art and science for the enhancement and embellishment of products. A convergence of scientific, artistic, material, economic, psychological, and market elements, contemporary packaging transcends its utilitarian roots. It is no longer solely driven by functional pursuits; instead, a paramount challenge is how to address the diverse needs of consumers – ranging from psychological and emotional needs to higher-level aesthetic and ecological considerations – while crafting packaging that exudes harmony, environmental consciousness, and health (Zhang et al., 2023; Zhu & Yu, 2021).

Against this backdrop, product life cycles have shortened, and the pace of product upgrades has accelerated. Enterprises increasingly adopt the production model of multiple varieties and small batches as the primary mode of operation. Simultaneously, consumer preferences have become more

DOI: 10.4018/IJITSA.346225

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diversified and individualized, with market segmentation emerging as a requisite survival strategy for enterprises (Qin et al., 2023; Wang et al., 2023; Meng et al., 2023). Notably, while there is considerable quantitative research on packaging design from a management and marketing perspective (Ketelsen et al., 2020), theoretical studies abound on the concept, connotation, and outlook of precise packaging design; however, practical investigations into specific application technologies, methods, and tools are sparse (Anukiruthika, 2020). Furthermore, existing studies often isolate explanations of packaging design's application within specific industries, neglecting the holistic coordination of the entire industrial environment encompassing design, production, sales, and waste disposal (Gu et al., 2022). Additionally, there is a paucity of research on the quantification of consumers' emotions. Consequently, the crux lies in leveraging modern digital technology to quantify customer aesthetic experiences in the packaging design process and establish a corresponding evaluation model. This, in turn, proves pivotal for enterprises seeking to minimize design and production costs, elevate management proficiency, and enhance market competitiveness.

Presently, the intricate quantitative relationship between user perception image demands and product modeling features is predominantly investigated through the application of computer-aided design to construct mathematical models. Notable methodologies include quantization I-theory (Chen et al., 2024), BP neural network (Yuan & Lee, 2020), and genetic algorithms (Gen & Lin, 2023). Wu (2020) conducted an analysis of users' needs utilizing the Likert scale, deconstructing their design features and employing a BP neural network to predict image modeling that aligns with users' perceptual requirements. Wen et al. (2023), aiming to achieve ceramic evolutionary design, seamlessly integrated genetic algorithms and executed quantitative design through selection, crossover, mutation, and other operations. Zhou et al. (2022) amalgamated factor analysis, cluster analysis, and BP neural network to establish a relationship model between modeling and perceptual image, facilitating a more precise perceptual evaluation of lawn mower modeling. Utilizing grey correlation and neural network, Hu (2020) delved into the mapping model between component modeling and single image, utilizing mobile phones as the design object to better guide the design direction.

While user image perception inherently possesses a strong element of fuzziness, existing efforts predominantly center on algorithmic enhancements and the mandatory use of fuzzy image perception information for precise numerical calculations. This approach broadens evaluators' scope to perceive cognitive deviations in imagery but tends to neglect prioritizing the exploration of fuzzy information processing in the modeling image fuzzy reasoning process. Building on the existing literature and prior investigations, the application of BP neural networks in product modeling primarily concentrates on household appliances, household goods, plane graphics, and similar domains, with limited studies on food packaging. Consequently, there is a necessity to leverage BP neural networks to delve into and design modeling within the context of food packaging.

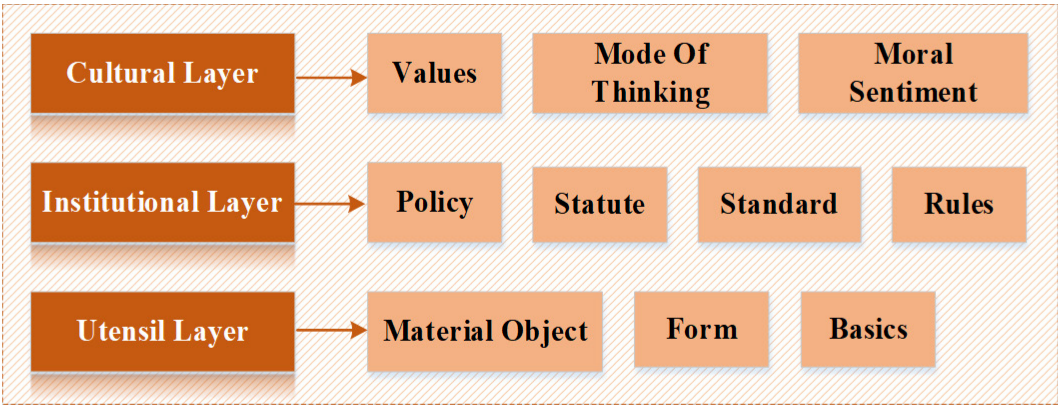
QUANTIFICATION OF AESTHETIC EXPERIENCE IN PACKAGING DESIGN

Cultural Form

Packaging constitutes a cultural factor intricately woven into commodity packaging. It transcends being a mere amalgamation of culture and packaging; rather, it represents a fusion of material and spiritual wealth manifested in the activities surrounding commodity packaging. In essence, packaging culture encapsulates humanistic ideals expressed through these packaging activities, with its core being the interplay and organic integration of economic endeavors and humanistic concepts. As illustrated in Figure 1, packaging culture manifests itself in three distinct forms.

Implementation layer: This layer embodies the culmination of packaging design activities, representing a tangible and comprehensible product form. It serves as the bedrock of the entire packaging culture. Oriented primarily towards marketing objectives, packaging culture integrates the creative endeavors encompassing social, economic, artistic, and psychological factors. It mirrors people's unified perception and creativity in packaging design, encapsulating a harmonious blend of

Figure 1. Forms of Packaging Culture



creation and aesthetics. Furthermore, it serves as a reflection of the developmental stage of productive forces within a specific societal context.

Institutional level: Packaging, as a social activity, undergoes a protracted process of design and production, giving rise to policies, regulations, standards, and rules that ensure and promote its efficacy. Organizational management establishes social norms, which, while not directly tied to cultural resources, ultimately derive their nature and developmental level from the dynamics of resource exchange within culture.

Within the aforementioned three levels of cultural structure, the implementation level and the system level manifest in external material forms that are readily perceptible. In contrast, the spiritual and cultural level is embedded in the psychological depths of individuals and groups, posing challenges for direct observation. Consequently, in the exploration of packaging culture, a dynamic examination of the multidimensional structure of cultural forms and their interactions is imperative. This approach corrects cognitive perspectives, enabling a deeper understanding of the consumption mentality prevalent in the packaging design market and guiding the practical aspects of packaging design.

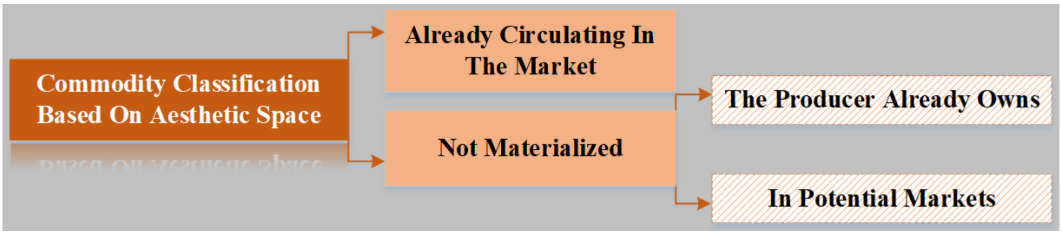
Spiritual and cultural layer: The spiritual dimension comprises values, thought patterns, moral sentiments, and other aspects cultivated by individuals through prolonged social practice and awareness activities. In the realm of packaging culture, concrete manifestations of people's requirements, wishes, emotions, cognition, and judgments during the purchase and utilization processes are discernible.

QUANTITATIVE PRINCIPLES OF AESTHETIC EXPERIENCE

The focus of the study on commodity quantification is the aesthetic space of commodities, which comprises numerous commodities. As illustrated in Figure 2, the commodities within the aesthetic space of commodities can be categorized into two groups: those that have been circulated in the market and those that have yet to materialize. The latter can be further subdivided into two categories: one is possessed by the producer, and the other exists within the potential market.

A commodity represents a synthesis of multiple attributes; however, within the aesthetic space of commodities, all attributes except for shape and color are considered uniform. The primary focus of aesthetic quantification research lies in the market, which comprises consumers. The assembly of commodities recognized by consumers within the aesthetic space is termed the aesthetic cognitive space, a dynamic entity that undergoes changes over time. It consistently remains a subset of the overall aesthetic space of commodities (Chen, 2021; Au, 2023). When consumers assess commodities within the aesthetic cognitive space, various aesthetic values, such as shapes and colors, can be compared, establishing a quasi-order relationship among commodities. In this context, as consumers conduct

Figure 2. Commodity Classification Based on Aesthetic Space



aesthetic evaluations at a specific moment, they identify the commodity with the highest aesthetic value, and the collection of such commodities is referred to as the consumer's aesthetic demand space.

At any given point, if the number of consumers perceiving the aesthetic value of a specific attribute of a commodity as the highest exceeds (or falls short of) that of another commodity, then the aesthetic value of this attribute is considered higher (or lower) than that of the other commodity. If there exists a subset within the aesthetic space of commodities wherein every consumer in the market can identify a product with the highest aesthetic value, and any product within this subset holds high aesthetic value in the market, then this subset is deemed the feasible aesthetic demand space of the market at that moment. The subset with the fewest elements represents the optimal aesthetic demand space for the market (Kang, 2020).

Quantitative Methods of Aesthetic Experience

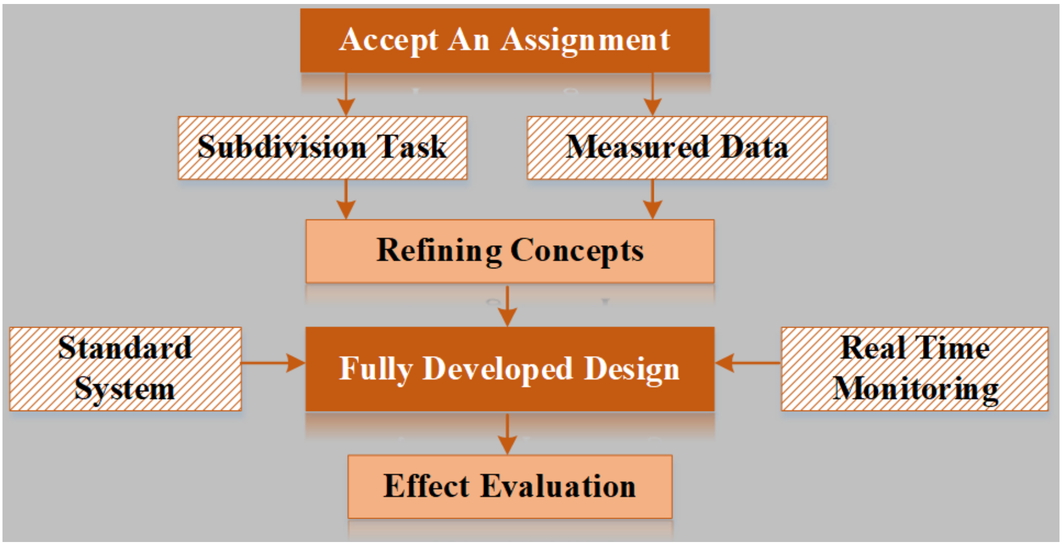
To undertake the research on aesthetic quantification, the initial step involves the quantification of the aesthetic space of commodities. Using the aesthetic space of packaging modeling as an illustrative example, let X denote the aesthetic space of packaging modeling, x represent the packaging design of a commodity, M denote a consumer in the market, t denote a specific time, and $XM(t)$ denote the aesthetic modeling demand space of M at time t. Additionally, let ρ_1 denote the distance on X, and the distance space X, ρ_1 must concurrently satisfy the following conditions:

(1) (P_1) (X, ρ_1) is a connected separable compact space;
(2) (P_2) $x_n(n = 0,1\cdots)$ is a sequence of points on X, where the distance between x_n and x_0 becomes smaller if and only if the materialization of x_n (n=0,1⋯) into the commodity y_n (n=0,1⋯), as n increases indefinitely. If a consumer begins to fail to distinguish the shape difference between y_n and y_0 by sense alone, the distance (X, ρ_1) is the aesthetic space of the product.

Let T_1 and T_2 be two time points, denote by $[T_1, T_2]$ the time period from T_1 to T_2, $X(t)$ is the commodity aesthetic space at time t, and the set of commodities that M can recognize in $X(t)$ is $M(t)$. It is the commodity aesthetic space of M at time t. Because the goods in the aesthetic space only consider the shape and assume other attributes to be the same, the aesthetic value of any commodity can be compared in the aesthetic space of consumers.

From the distance in commodity aesthetic modeling space (X, ρ_1), it can be known that the smaller (or larger) the distance is, the smaller (or larger) the morphological difference of some aesthetic elements among commodities is. This kind of distance divides the commodity aesthetic space into several separable compact spaces, which indicates that at any moment, a limited number of commodities can be used to approximate the infinite number of commodities in the commodity aesthetic space. Thus, we can know the aesthetic space form of packaging.

Figure 3. Design Process of Packaging Style



DESIGN OF PACKAGING STYLE BASED ON QUANTITATIVE AESTHETIC EXPERIENCE

Design Process

The design process of packaging style based on quantitative aesthetic experience is depicted in Figure 3.

Initiate the design task by defining it, decompose the task using precision concepts, and establish design details from diverse index systems. Simultaneously, precisely manage design objectives, define the division of labor, and establish cooperation within the design team. This sets the groundwork for the seamless progression of the design task and ensures the quality assurance of the outcomes.

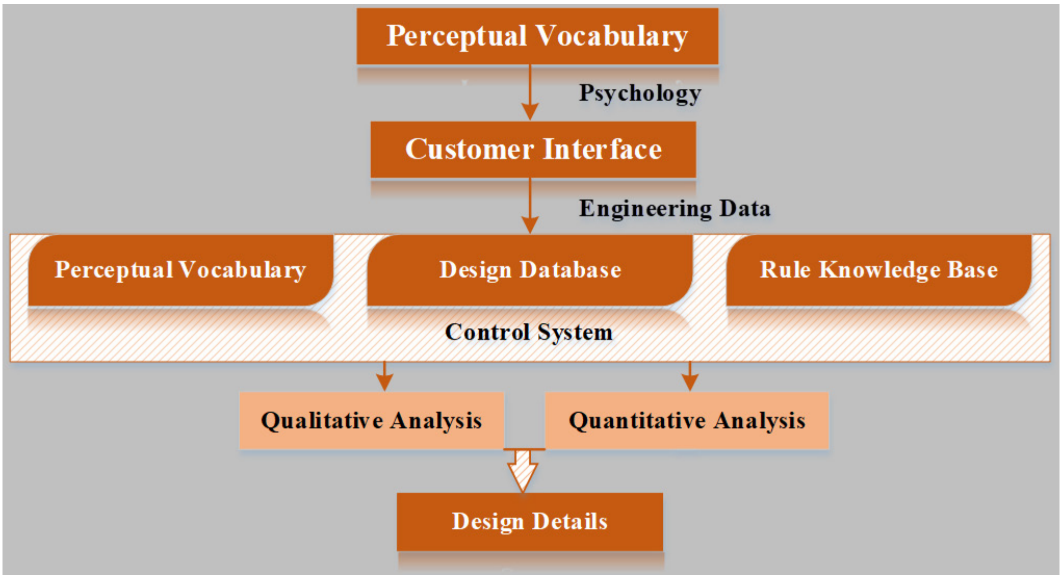
Precision in design relies on data. To ensure accuracy and scientific rigor in design outcomes, establish a comprehensive measurement system. Equip measuring instruments, enhance the data acquisition system, and standardize the processes for data collection, analysis, and utilization (Feroz & Dabous, 2021). Leveraging the measurement management system enables the realization of a management model encompassing "data collection, data analysis, data control, and data management." Data types include consumer aesthetic experience data, market trend data, similar product data, enterprise management data, and industry-level data.

Utilize quantitative data on customers' aesthetic experiences to categorize packaging styles. Combined with the current technical landscape, formulate a refined design concept. The design process should be collaborative, involving information sharing and communication among different groups or individuals. Refine detailed parameters of the packaging design process throughout the design journey.

The specific implementation method is shown in Figure 4.

For the effective implementation of this design method, it is imperative to comprehend consumers' genuine sentiments regarding products based on data measured through machine learning and psychological theory. The objective is to capture consumers' preference information rooted in their aesthetic experiences. Concurrently, the establishment of ergonomic technology is crucial to align with societal transformations and people's evolving preference tendencies. A vocabulary reflecting customers' aesthetic experiences is collected and processed to construct diverse databases.

Figure 4. Implementation Process of Packaging Style Design



Subsequently, design rules corresponding to the design elements are established, culminating in the eventual production of products.

Model Design

In traditional packaging design, the formulation of packaging form primarily relies on the creative ideation of designers. In contemporary packaging design, intelligent design technology for packaging image modeling has emerged, significantly enhancing product design efficiency through the integration of emotional quantification technology. The application of BP neural networks enables designers to comprehend the intricate relationship between consumers' emotional experiences and packaging design elements. Consequently, designers can ascertain pertinent design details based on these established relationships (Chen et al., 2022; Yang et al., 2021).

Adjective Matching

Prior to embarking on packaging design, it is essential to curate a semantic set of adjectives that precisely encapsulate customers' sentiments and aesthetic preferences. An excess of adjectives can hinder the precise articulation of packaging modeling images; thus, it becomes imperative to streamline the image description space further. Table 1 delineates the adjective matching employed in this paper.

Calculation of Emotional Depth

Each digital image corresponds to a color histogram, and different images may have the same color distribution, leading to identical color histograms. The global color histogram of a digital image is the sum of its local color histograms. However, individual local histograms can only provide information about the frequency of occurrence of certain colors within specific regions of the image and cannot reflect spatial information about the location of pixels.

Assuming that the retrieved image in the image library is I, and the key image submitted by the user is Q, this topic uses the histogram intersection formula (4) to calculate the similarity of two images:

$$S(H_I, H_Q) = \sum_{i=0}^{N-1} \min\left(H_I(i), H_Q(i)\right) \tag{1}$$

Table 1. Description of Emotional Space

Number	Adjective	Matching words
1	Romantic	Rational
2	Modern times	Tradition
3	Flow line	Geometry
4	Bright-colored	Simple but elegant
5	Abstract	Concrete image
6	Harmonious	Conflict
7	Strong	Moderate
8	Fashion	Simple
9	Passion	Calm
10	Terse	Complex

The following formula (2) is used to normalize the similarity degree of two images, ensuring that the similarity degree is in the range of [0,1].

$$S\left(I,Q\right) = \frac{\sum_{i=0}^{N-1} \min\left(H_I\left(i\right), H_Q\left(i\right)\right)}{\sum_{i=0}^{N-1} H_Q\left(i\right)} \tag{2}$$

where $H_I\left(i\right)$ refers to the i-th handle histogram of image I, and $H_Q\left(i\right)$ refers to the i-th handle histogram of image Q, $i \in [0, N-1]$. $S(I,Q) \in (0,1)$ represents the similarity of two images; if the two images are more similar, the value of S(I,Q) is closer to 1. If the two images are identical, $S(I,Q) = 1$.

The data analysis model of each emotion is as follows:

$$\rho_{xy} = \frac{\mathrm{cov}(x,y)}{\sqrt{D(x)}\sqrt{D(y)}} \tag{3}$$

$$\mathrm{cov}\left(x,y\right) = E\left\{\left[A_{ix} - E(A_{ix})\right]\left[A_{iy} - E\left(A_{iy}\right)\right]\right\} \tag{4}$$

$$D\left(x\right) = E\left[A_{ix} - E(A_{ix})\right]^2 \tag{5}$$

$$E(A_{ix}) = \frac{1}{I}\sum_{i=1}^{I} A_{ix} \left(x = 1,2,\cdots,j,\cdots,J; y = 1,2,\cdots j,\cdots,J\right) \tag{6}$$

Where, A_{1j}^k is the j-th perceptual preference of the k-th respondent to the i-th investigation case, and A_{ij}^k is the evaluation of "appreciation" and "disapproval" of the i-th investigation case.

According to the calculation result of the above formula, analyze it by the test method of correlation coefficient. When x = 1, 2, ... j – 1, j, or y = j, $\alpha = 5\%$, and the correlation coefficient is ρ_1. Because there is negative correlation, when $|\rho_{xJ}| > \rho_1$, it can also be considered that the emotion value x is related to the sensibility of the survey object; otherwise, it is not related and can be removed. When x = 1, 2,..., j., j - 1 and y = 1, 2,..., j., j - 1, when $|\rho_{xJ}| > 0.9$, it can be considered that the emotion value x is completely correlated with the emotion value y. The description of perceptual data is shown as follows:

$$\begin{bmatrix} A_{11} & A_{12} & A_{13} & \cdots & A_{1M} \\ A_{21} & A_{22} & A_{23} & \cdots & A_{2M} \\ & \cdots & & A_{im} & \cdots \\ A_{I1} & A_{I2} & A_{I3} & \cdots & A_{MM} \end{bmatrix} \tag{7}$$

Factor Analysis

While the cognitive model established by treating all the aforementioned perceptual evaluation values as independent factors comprehensively captures consumer perceptual information, it can become overly intricate, leading to slow statistical processes. Hence, there is a need to diminish the dimensions of the perceptual model and streamline the structure of the cognitive model through the aid of factor analysis.

The factor analysis model is established according to the evaluation information data matrix:

$$A_i = (\text{Factori})B_i + e_i \tag{8}$$

Where A_i is the case data matrix, and $A_i = [A_{i1}, A_{i2}, \cdots, A_{im}, \cdots, A_{iM}]^T$, B_i is the factor coincidence coefficient matrix:

$$B_i = \begin{bmatrix} B_{i11} & B_{i22} & \cdots & B_{i1n} & \cdots & B_{i1N} \\ B_{i21} & B_{i22} & \cdots & B_{i2n} & \cdots & B_{i2N} \\ & & \cdots & & & \\ B_{iM1} & B_{iM2} & \cdots & B_{iMnn} & \cdots & B_{iMN} \end{bmatrix}$$

Factori is the factor matrix that $\text{Factori} = [\text{Factor1}_i, \text{Factor2}_i, \cdots, \text{FactorN}_i]^T$, e_i is the residual, $e_i = [e_{i1}, e_{i2}, \cdots, e_{im}, \cdots e_{iM}]^T$, n is the number of factor, $n = 1, 2, \cdots, N$

To identify representative words from an extensive dataset, we conduct a subsequent cluster analysis of the factor load within each vocabulary group. By comparing the related characteristics of various elements, the study aims to classify different entities. This involves grouping similar individuals into the same category and segregating individuals with substantial inherent differences into distinct categories. The establishment of the distance model for cluster analysis is based on the coordinates of each emotional word in the factor space, as articulated in formula (9):

$$d_{uv} = \left[\sum_{n=1}^{N} (B_{un} - B_{vn})^2\right]^{\frac{1}{2}} \tag{9}$$

Style Prediction Based on Neural Network

The neural network is established with a composition of four layers: one input layer, two hidden layers, and one output layer. The node structure follows “8→4→16→1,” where the input layer is a combination of 8 elements, and the output layer represents the target value. The first hidden layer comprises 4 neurons. The tangent sigmoid transfer function is employed, and the neuron output is expressed in formula (10):

$$y_j = \text{tansig}\left(b_j + \sum_{i=1}^{8} \omega_{ij} x_i\right) \tag{10}$$

Where i = 1, 2,..., 8; j = 1, 2, 3, 4; ω_{ij} is the connection weight between neuron i and neuron j; b_i is the threshold; y_i is the output of hidden layer neurons; x_i is the ith neuron. Hidden layer 2 has 16 neurons.

The log-sigmoid transfer function is selected, and the output of neurons is shown in formula (11):

$$y_k = \text{logsig}\left(b_j + \sum_{j=1}^{4} \omega_{jk} y_j\right) \tag{11}$$

Where j = 1, 2, 3, 4; k = 1, 2,..., 16; ω_{jk} is the connection weight between neuron j and neuron k; y_k is the output of neurons in the output layer; b_i is the threshold; y_i is the output of hidden layer neurons.

Purelin transfer function is selected for the output layer, and the final output result is shown in Formula (12):

$$y = b + \sum_{k=1}^{16} \omega_k y_k \tag{12}$$

Where k = 1, 2,..., 16; ω_{ij} is the connection weight between neuron i and neuron j; ω_k is the weight of neuron k; y_k is the output of neurons in the output layer; b is the threshold.

The batch size of each input to the model is set to 32. The stochastic gradient descent algorithm is used to optimize the network, the weight decay is set to 0.0005, and the learning rate is set to 0.001. The Dropout strategy and L2 paradigm are used in the model to prevent overfitting, and the Dropout value is set to 0.5.

Evaluation Model

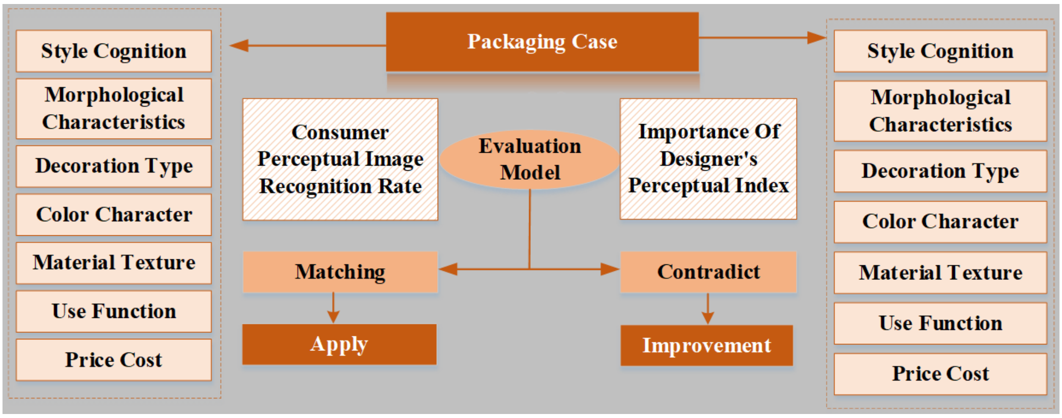
Design and evaluation of packaging are two distinct yet interconnected processes. To harness the full potential of evaluation, it is imperative to establish a scientific and precise evaluation system for packaging. This involves assessing existing packaging design cases, aligning the recognition rate of consumers' perceptual images with the significance of designers' aesthetic experiences. Evaluation results are then obtained based on the degree of alignment, testing the realization of design goals, as illustrated in Figure 5.

Through the evaluation index shown in Figure 5, the product is evaluated according to the packaging design process based on its market competitiveness. This model mainly evaluates the satisfaction degree of products or services in this industry from the perspective of customers and can show the strengths and weaknesses for improvement of existing products or services in the market.

CASE ANALYSIS

Tea packaging embodies the multifaceted nature of product packaging within the broader context of consumer goods. With tea being a globally consumed beverage, its packaging intricately addresses consumer sensitivities regarding freshness, flavor preservation, and cultural nuances. The diverse array of tea products, from traditional loose-leaf blends to contemporary herbal infusions, allows for an exploration of packaging formats tailored to distinct market segments. Furthermore, the cultural significance of tea provides insights into how packaging design incorporates elements to resonate with specific audiences. As the tea industry grapples with environmental concerns, examining tea packaging

Figure 5. Evaluation Model of Packaging Style Design Based on Quantitative Aesthetic Experience



offers a lens through which to discuss sustainable materials and eco-friendly practices. Additionally, tea packaging serves as a compelling case study to understand how branding elements contribute to market differentiation and competitiveness. Thus, delving into the nuances of tea packaging provides a rich and comprehensive context for exploring the broader implications and challenges of effective product packaging in the consumer goods landscape.

In this study, tea packaging design is chosen to validate the efficacy of the design model. A total of 100 participants, 60 males and 40 females, are selected from various segments of society. Among them, 40 are tea enthusiasts, 35 are occasional tea drinkers, and 25 are rare tea drinkers. This structured selection aims to ensure the scientific and representative nature of the survey results. It fully accounts for the similarities and differences in the aesthetic experiences of different demographic groups concerning tea packaging culture.

Model Training Results

Compare the aforementioned 100 test subjects with the emotional scores obtained after model regression, and the results are depicted in Figure 6. The regression data is represented in red, while the training data is depicted in black.

The figure reveals that the majority of the predicted data errors within the training set fall within the range of 0.2. This indicates that the model exhibits a robust fitting regression effect with high prediction accuracy. It establishes a reliable mapping relationship between the semantic space of user perceptual images and product modeling design elements. Consequently, this model proves suitable for the automatic fitness evaluation of product image morphological evolution design.

Results of Factor Analysis

Following the factor analysis process outlined earlier, the factor scores for this case are obtained, as illustrated in Table 2.

From the results of factor analysis in the above table, it is evident that the image vocabulary of this batch of tea packaging is primarily explained by three factors, with each factor carrying a distinct representative meaning.

Model Comparison

Cluster analysis results are presented in Table 3. From the table, it is evident that three pairs of words describing perceptual images are ultimately extracted: “harmony-conflict,” “abstraction-

Table 2. Factor Analysis Results

Factor	Emotional vocabulary	Factor load		
A	Bright-colored	0.980	0.123	0.063
	Modern times	0.920	0.196	-0.032
	Flow line	0.937	0.204	-0.094
	Romantic	0.839	0.498	0.374
	Concrete image	0.893	0.363	0.532
	Harmonious	0.790	0.439	0.124
B	Strong	0.634	0.468	0.343
	Conflict	0.443	0.346	-0.082
	Passion	0.343	0.167	-0.073
	Simple but elegant	-0.244	-0.172	0.321
	Abstract	-0.487	-0.283	0.472
C	Moderate	-0.283	-0.578	0.899
	Terse	0.055	0.382	0.984
	Fashion	0.021	0.374	0.942
	Geometry	0.027	0.127	0.929

Figure 6. Prediction Results of Our Model

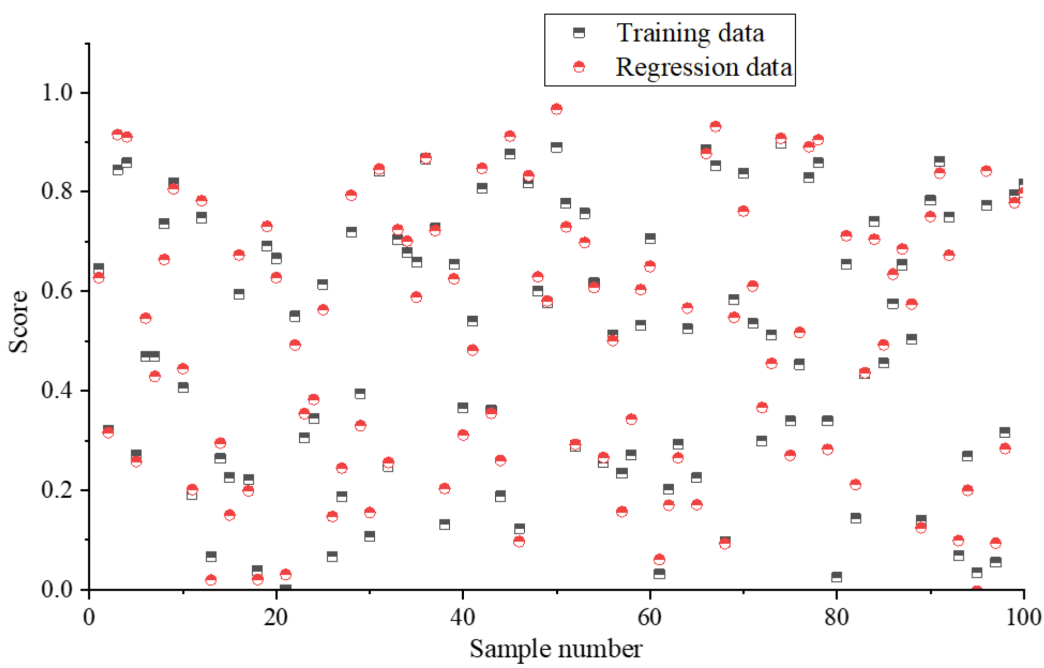


Table 3. Cluster Analysis Results

	Category	Distance
Harmonious	A	0.138
Flow line	A	0.082
Romantic	A	0.121
Abstract	B	0.123
Bright-colored	B	0.021
Strong	A	0.127
Terse	A	0.108
Modern times	C	0.243
Fashion	B	0.179
Passion	C	0.256

concreteness," and "modernity-tradition." This marks the completion of emotional positioning and description for tea packaging modeling.

As shown in Figure 7 and Figure 8, when comparing our model with BP and DNN models (Messner, 2023; Kuo et al., 2021) across various features, it becomes evident that our model demonstrates significant advantages in multiple aspects.

First, in the features of harmonious and flow, our model achieves scores of 0.09508 and 0.06629, respectively, surpassing other models. This suggests that our model excels in capturing the harmonious and flowing characteristics in artwork, potentially offering a superior sense of overall aesthetics and fluidity. Second, in the features of romantic and abstract, our model also exhibits high scores (0.08813 and 0.06366), outperforming other models, especially those of Messner (2023) and Kuo et al. (2021). This implies that our model possesses a unique ability to capture romantic and abstract elements, making it more suitable for artwork with these emotional and stylistic attributes. Furthermore, for the features terse and modern, our model presents high scores (0.08673 and 0.08506), suggesting that our model excels in capturing concise and modern elements. This makes it suitable for artwork with a more succinct and contemporary aesthetic. Finally, in the features of strong and fashion, our model achieves scores of 0.09578 and 0.08644, respectively, surpassing other models. This may indicate that our model performs exceptionally well in expressing strong and fashionable characteristics in artistic creations.

Through this comparative analysis, it is evident that our model excels across various artistic features, showcasing superiority in aesthetic perception and artistic aesthetics. These results provide robust support for the widespread application of our model in the field of art generation.

Results of Neural Network Training

The design elements of tea packaging based on aesthetic experience are detailed in Table 4. The combination of case elements are fed into the neural network from the input layer, and the network will output the predicted value. Upon comparison with the data acquired from the questionnaire, it is observed that they are largely consistent. This underscores the correctness and effectiveness of the neural network-established mapping of design element-emotional evaluation.

The clustering results reveal that the intention value of harmony-conflict is the highest, with the minimum emotional value for the case under this emotion matching being 2.342, and the maximum reaching 6.781. The results of the element design combination are detailed in Table 5.

Figure 7. Results of Emotional Vocabulary Training in Traditional Models

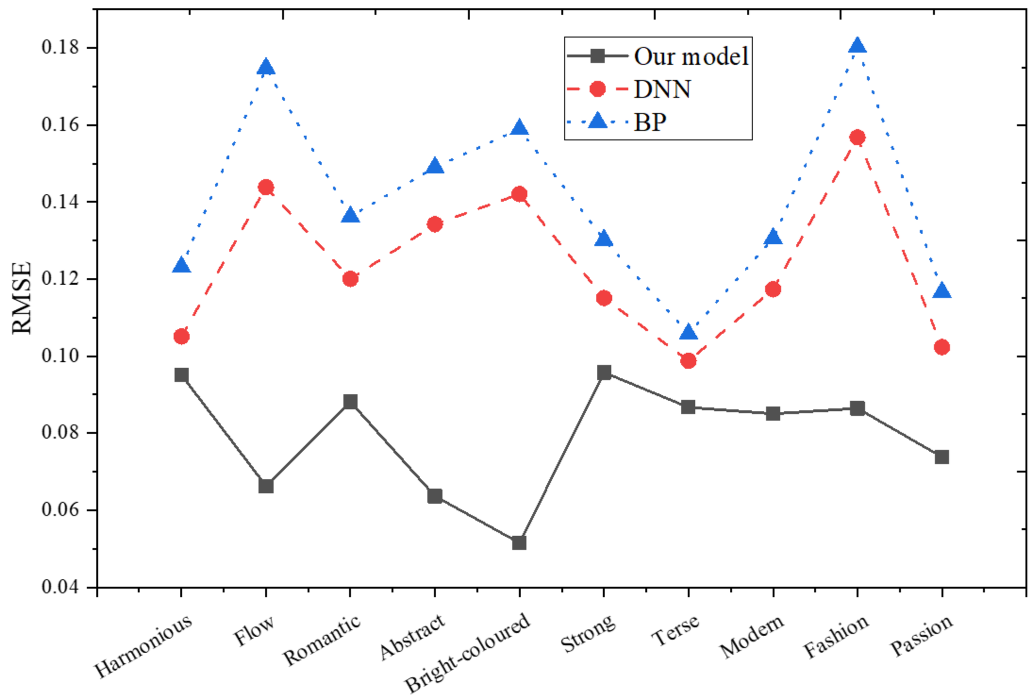


Figure 8. Results of Emotional Vocabulary Training in Different Models

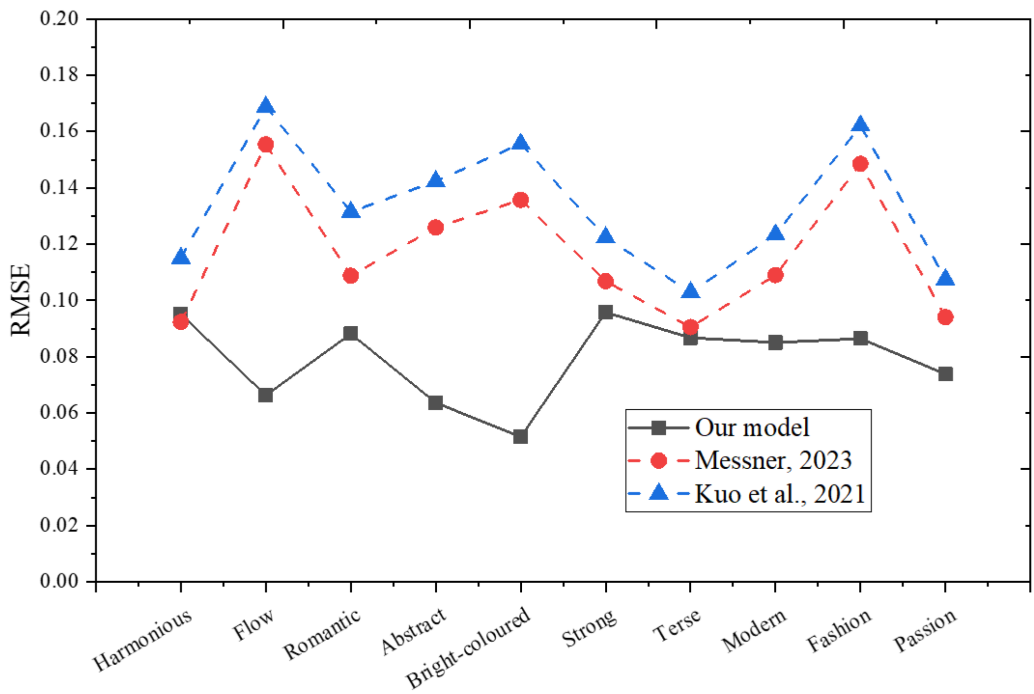


Table 4. Design Elements of Tea Packaging

Classify	Element	Type 1	Type 2	Type 3
Appearance Effect	Colour	Cool Colour	Warm Colour	No Color
	Style	Straight Line	Flow Line	Square
Morphological Character	Proportion	1:1.5	1:2	1:2.5
	Handle Form	Rope	Digging Hole	No Handle
Panel Relation	Panel Matching	Plane	Curved Surface	Irregular
	Panel Relevance	Independence	Unify	Local Unification

Table 5. Design Combination Results of Elements

Classify	Element	Harmonious combination	Conflict combination
Appearance effect	Color	Warm color	No color
	Style	Flow line	Straight line
Morphological character	Proportion	1:1.5	1:2
	Handle form	No handle	No handle
Panel relation	Panel matching	Plane	Plane
	Panel relevance	Unify	Local unification

Notably, the matching between the handle form and the panel exhibits a unified feature, suggesting a low impact on harmony-conflict. Thus, emphasis in the design process should be directed towards other elements.

The proposed packaging style design method and evaluation model offer a versatile solution with broad applications beyond the realm of tea. By prioritizing cost efficiency, sustainability, and brand image, these tools provide a comprehensive framework adaptable to various industries, including cosmetics, electronics, pharmaceuticals, and more. The emphasis on supply chain optimization, customization, and regulatory compliance ensures flexibility in the face of evolving market dynamics. Furthermore, the model's focus on waste reduction addresses a universal concern. Overall, this approach encourages cross-industry innovation, offering a practical and holistic guide for companies aiming to enhance their packaging strategies, reduce environmental impact, and meet the evolving demands of consumers and regulatory bodies.

CONCLUSION

This paper introduces the cultural aspect of product packaging, elucidating the quantitative principles and methods of customers' aesthetic experiences. It proposes a method for packaging style design and an evaluation model based on quantitative aesthetic experiences. Using tea packaging design as an example, the model is verified through case analysis. The results of the case analysis demonstrate that the neural network-established mapping of design element-emotional evaluation is accurate and effective. The clustering results reveal that the intention value of harmony-conflict is the highest. Under this emotional matching, the case's emotion values range from a minimum of 2.342 to a maximum of 6.781. In the combination of design elements, emphasis should be placed on the unity of the handle form and the panel, while other elements require careful consideration during the design process.

Future research in packaging design should focus on advancing our understanding of cultural influences by exploring cross-cultural variations in aesthetic preferences, integrating neuroaesthetics principles for a deeper understanding of the neurological basis of aesthetic experiences, tracking dynamic shifts in aesthetic trends over time, incorporating sensory elements like touch, smell, and sound into design considerations, developing AI-driven tools for culturally sensitive designs, examining the intersection of environmental sustainability and aesthetics, implementing consumer co-creation approaches, and refining emotional impact assessments through advanced technologies. By addressing these dimensions, researchers can contribute to a more comprehensive and adaptive framework that enhances the effectiveness of packaging design in diverse cultural contexts and aligns with evolving consumer preferences and societal values.

CONFLICTS OF INTEREST

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

FUNDING STATEMENT

No funding was received for this work.

PROCESS DATES

05, 2024

Received: This manuscript was initially received for consideration for the journal on 01/10/2024, revisions were received for the manuscript following the double-anonymized peer review on 02/19/2024, the manuscript was formally accepted on 03/21/2024, and the manuscript was finalized for publication on 05/01/2024

CORRESPONDING AUTHOR

Correspondence should be addressed to Fang Wu; 15826345825@163.com

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