

Research Article

On the Prediction of Product Aesthetic Evaluation Based on Hesitant-Fuzzy Cognition and Neural Network

Xinying Wu ¹, Minggang Yang, ¹ Zishun Su ^{1,2} and Xinxin Zhang ³

¹School of Art, Design and Media, East China University of Science and Technology, Shanghai, China

²Shanghai Business School, 2271 West Zhongshan Rd., Shanghai, China

³School of Architecture and Art Design, Hebei University of Technology, Tianjin, China

Correspondence should be addressed to Xinying Wu; y10170069@mail.ecust.edu.cn

Received 9 January 2022; Revised 18 April 2022; Accepted 30 April 2022; Published 20 June 2022

Academic Editor: Ning (Chris) Chen

Copyright © 2022 Xinying Wu et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Product market competitiveness is positively influenced by the aesthetic value of product form, which is closely related to product complexity. By measuring the cognitive complexity of the product, this research establishes the relationship between the complexity and aesthetics of the product using an artificial neural network. Hence the prediction of product beauty is achieved, which guides design decisions. In this article, the complexity of product form is first measured through a combination of hesitant-fuzzy theory and information axiom. Afterward, the result is weighted by exponential entropy and dimensionally compressed. This method makes data more suitable for the prediction with small samples, obtaining an accuracy improvement of up to 40% compared with traditional approaches. Finally, the importance order of the design elements which affect morphological complexity is acquired. Results show that three of the six complexity features (element number, object intelligence, and object detail) are more significant, impacting the aesthetic feeling of product form. The method increases the attractiveness of products to customers, providing valuable design support for enterprises and designers in the early days when a new product is designed, and reducing research and development risks.

1. Introduction

In recent years, the study of aesthetic and complexity has attracted extensive attention from scholars in the fields of industrial design, psychology, and industrial engineering. There is a specific implicit correlation between aesthetic and complexity [1], where the complexity affects aesthetic feelings of people [2]. In aesthetic process, people will judge the aesthetic scale of the aesthetic object through visual cognition [3], thus, cognitive differences between the complexity of the product form, which is termed as cognitive complexity, and the objective form complexity and aesthetic evaluation are produced. The cognitive complexity can directly reflect the aesthetic degree of an aesthetic object, and too high or too low cognitive complexity will not bring a pleasant aesthetic experience [4]. However, most existing studies focus on the calculation of the complexity and beauty of the structure ontology [5] and seldom consider the

complexity measurement after visual cognitive processing, which is critical for the overall aesthetic evaluation of a product and has a direct impact on user experience and preference. Therefore, research on the quantification of cognitive complexity is urgent, and how to better quantify the complexity of a product after user perception has become a key consideration for product development.

The core of product design is to meet customer needs [6]. The designers used to develop and design products relying on their own experiences and tastes, which results in problems such as incomplete cognition and unequal aesthetic information of consumers. Thus, more than 80% of the latest products will face failure in the fast-changing consumer market [7]. Suh [8] proposed the design-centric complexity theory (DCC) based on axiomatic design theory, which focuses on the study of complexity generation in the design process [9], providing theoretical support for the quantification of visual cognitive complexity. In practical

applications, the process to measure users' affective cognition suffers from high complexity and uncertainty and cannot directly obtain accurate values as the DCC model requires exact values. The DCC model is limited in measuring user cognitive complexity. This study combines the DCC model with hesitant-fuzzy theory to quantify the hesitation raised in user perception to overcome this problem.

This method takes customer perceived aesthetics as the prediction index. It uses a neural network to establish a prediction model of the relationship between visual cognitive complexity and customer perceived aesthetics, which can effectively reflect the potential relationship between user perceptual aesthetics and product complexity design rules, to reduce the failure probability of new products and optimize product form design. In the process, dimension compression was adopted to handle the sample data. A good training effect was finally achieved using small sample data. The proposed method addressed the problem that users' perceptual data in traditional perceptual engineering is difficult to collect, and the amount of data is generally small, which cannot meet the requirements for machine learning.

The technical route adopted in this study is as follows. First, accurate user perceptual and cognitive needs are explored. The complexity principles affecting product modeling are collected according to relevant literature. Using the characteristic of hesitant fuzziness of user perceptual cognition, we applied the semantic difference (SD) method to evaluate user perceptual cognition. Second, a complexity calculation model of product form is established. The hesitant-fuzzy theory and the DCC model are combined to build the product form complexity model. Then, the model is used to measure the collected user perceptual data to complete the measurement of product complexity. Finally, a machine learning prediction method using a small sample is proposed. A combination of PCA algorithm and exponentially weighted entropy method is used to effectively compress the collected user perceptual data. The results show that the accuracy of the predicting model is improved by more than 40%, indicating the feasibility of the proposed model.

In summary, the main contributions and innovations of our works are as follows:

- (1) In product design, the hesitant-fuzzy linguistic term set and DCC model are combined to measure the complexity after user cognitive processing, achieving a practical quantitative effect and dramatically reducing subjective factors' influence.
- (2) A machine learning approach is used to develop product form beauty predictions using neural networks. A relationship between beauty and complexity is established. An exponentially weighted entropy was used to calculate the complexity principle and demonstrate a complexity index importance ranking to guide designers in the initial development of product design.
- (3) A new data dimensional compression method is proposed, which overcomes the problem of small

user perceptual data and difficulty in machine learning. A feasible small sample training method is constructed to improve the prediction accuracy significantly.

The rest of the article is organized as follows: in Section 2, some relevant research is introduced. In Section 3, the technical route of this study is shown. Later in Section 4, the case analysis and comparative verification are conducted. Finally, the article is concluded in Section 5.

2. Related Works

2.1. Cognitive Complex System. The cognitive complex system of the human brain has strong coupling and nonlinear characteristics, which involves the synergy of multilevel complex cognitive system [10] as is the same with visual cognition. Newell and Shaw [11], and Donderi [12] viewed that visual complexity is related to visual information acquisition, data integration, and perceptual processing, which was applied in aesthetic measurement [13].

In current researches, visual cognitive complex systems mainly focus on two aspects:

- (1) the manifestation of visual complexity and
- (2) the relationship between complexity and attention.

As for the first aspect, the complexity of vision is multidimensional, and it can be divided into ontology and derivative complexity [14]. Ontology complexity is the complexity of an object's structure, system, and information volume, and derivative complexity can stimulate different emotional responses in the cognitive system, which is directly affected by the complexity of the ontology. To investigate the influence of visual complexity on emotion, Berlyne and Maher [15] experimented on the complexity of product modeling. They found that the complexity can affect the arousal and pleasure of the subjects' emotions, and the complexity of emotion and modeling presents an inverted U-shaped curve. Based on the cognitive model that Berlyne proposed, Baxter [16] found that it is the complexity perceived by the human brain after cognitive processing instead of the perceptual cognition caused by product that form the direct complexity of the product.

For another aspect, visual attention, as an essential optical characteristic, plays a vital role in human visual perception [17]. When the form of a cognitive object has a medium complexity, human cognitive ability, and attention degree can reach the highest level [18]. These contribute to aesthetic recognition for users. For example, Hagerhall et al. [4] concluded that human visual cognition is more inclined to the figure under a dimension of 1.3. Sun et al. found that there is a nearly monotonous relationship between visual complexity and aesthetic expectation [19]. In the complex system research of product, the DCC model is guided by users' cognitive needs and can be used to measure the complexity of product form [8]. Compared with other evaluation and measurement methods, DCC does not need the decision-maker to determine the index weight for

discrimination [6], which weakens the influence of human subjective factors. By calculating the amount of the product system information, the measurement of product complexity can be achieved.

The studies above show the research value association between visual cognitive complexity and beauty of product form. However, there are some limitations. Although DCC provides a specific theoretical regulation for designers to quantify the complexity of products, an accurate value is required to calculate, which is not available for fuzzy value calculation. While in the research of product complexity calculation, human perceptual cognition was absent, and user emotional needs were not considered. Therefore, combining the DCC model, we proposed a new method for quantifying cognitive complexity suitable in the product field: (1) Perceptual variables in the visual cognitive data acquisition link are introduced, which more fits people's actual perceptual needs increases the experimental reliability. (2) Considering the influence of cognitive hesitation fuzziness, the DCC model was combined with hesitant-fuzzy theory, enhancing the usability.

2.2. Hesitant-Fuzzy Theory. The fuzzy algorithm was proposed by Zadeh [20] to solve the problem of nonlinearity and uncertainty, which has been used widely in product design to perform fuzzy reasoning on user cognitive ambiguity [21–23]. It can establish an accurate relationship between the actual psychological intention and the product characteristics in cognitive processing. However, when measuring the complexity of product form, many uncertain factors occur. The system is random, fuzzy, and hesitant, and it is hard to determine the specific value of the index accurately. As depicted in Figure 1, in the process of perceptual cognition, the aesthetic standards of product form (complexity, order, etc.) are produced by the visual region of the human brain, and the prefrontal cortex finally makes the aesthetic decision [24]. The whole cognitive process is accompanied by the interference of hesitant and fuzzy factors. Thus the results obtained are subject to bias depending on traditional perceptual engineering measurements.

Most scholars applied fuzzy mathematical methods to quantify perceptual indicators to solve this problem accurately. Kulak and Kahraman [25] used the concept of fuzzy logic to quantify perceptual variables using affiliation functions to achieve an accurate measurement of user perception. Shen and Wang [26] proposed a combination of fuzzy language and perceptual data to deal with the fuzzy problem in decision-making. The literature [27] presented fuzzy linguistic summarization, which defined fuzzy rules and correlated the rules with users' affective needs to capture their actual perceptual needs. Although the above studies considered the fuzziness generated by user perceptions, they paid less attention to the uncertainty and hesitation raised by user perceptions in the process. In the actual measurement process, much of the information about users' perceptual cognition is challenging to accomplish quantitatively. In our interviews with users, people are found to be more likely to use verbal descriptions to evaluate indicators or decisions,

which is consistent with the ambiguity of human thinking. At the same time, there is often a strong sense of hesitation and uncertainty in the user's decision-making process. The decision-maker will hesitate between multiple linguistic terms, requiring more complex linguistic terms to express the decision [28]. There are limitations to accurately quantifying fuzzy information using only the fuzzy mathematical principles. However, this can be overcome by the hesitant-fuzzy theory.

For example, Wang and Zhao [29] used a combination of hesitant-fuzzy theory and consensus models to achieve decision information integration. Similarly, the hesitant-fuzzy theory is often combined with different evaluation models for ambiguity problems analysis. Liao et al. [30] combined hesitant-fuzzy theory with the VIKOR method to make decision evaluations, and Beg and Rashid [31] extended hesitant-fuzzy linguistic decision-making to the Topsis method. In perceptual engineering, the hesitant-fuzzy theory has also been applied to quantify users' perceptual decisions. For example, Hirokawa et al. [24] introduced the hesitant-fuzzy theory in perceptual engineering to quantify users' perceptual evaluations of product styling. This shows that: (1) Hesitant-fuzzy theory is very helpful for quantifying uncertain information triggered by user perception and dealing with fuzzy problems in decision-making, which can greatly reduce the influence of subjective factors on the outcome. (2) Hesitant-fuzzy theory can be combined with a variety of methods and is more flexible. In hesitant-fuzzy theory, a language term can only correspond to one variable or index and cannot establish a mapping relationship with complex indexes, schemes, variables, and so on. Therefore, based on hesitant-fuzzy language, Rodriguez et al. [32] proposed hesitant-fuzzy linguistic term sets (HFLTSS) to solve the cognitive fuzziness caused by multifactor hesitation. When users are hesitant about multiple language terms, HFLTSS can make the qualitative judgment more accurate and help decision-makers make effective decisions. Therefore, this article uses the HFLTSS to measure users' perceptual cognition.

Moreover, in product design, the research on the combination of fuzzy theory and the DCC model is still absent. The DCC model requires a definite value to calculate. At the same time, hesitant-fuzzy theory can make users' evaluation of indicators accurate and meet the calculation requirements of the DCC model. So, we combined the DCC model with hesitant-fuzzy theory. The proposed method solved the limitations of DCC theory on the one hand.

On the other hand, the problem of users' cognitive hesitation fuzziness is addressed. Compared with the research on single users' fuzziness, our proposed method is more comprehensive and objective, despite some shortcomings such as the difficulty of collecting data. Therefore, it is necessary to study the small sample prediction method in the follow-up research.

2.3. Intelligent Beauty Evaluation. Artificial intelligence is extensively used in various fields with the breakthrough of technology. The field of aesthetics is different from other

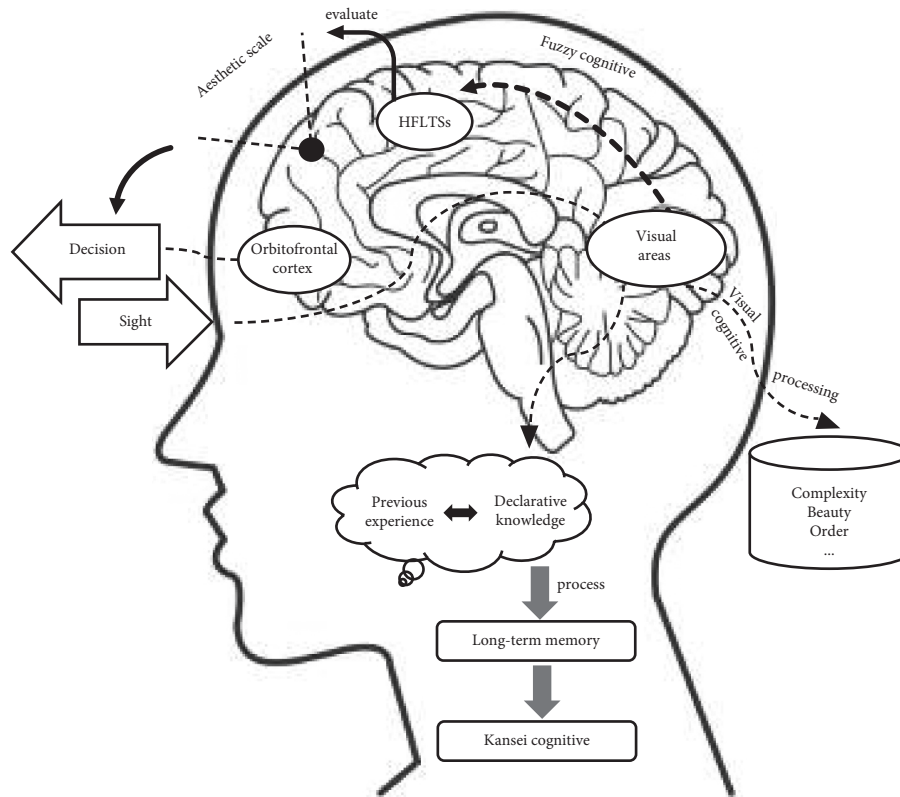


FIGURE 1: The decision-making process of the human brain after hesitant and fuzzy cognition.

fields because it needs to combine psychology and sociology with exploring human brain cognition. At present, aesthetic sense has become the core of human-computer interaction. The analysis and calculation of visual aesthetic models have been widely concerned [33]. A large number of studies have been conducted on image aesthetic quality evaluation [34], including web aesthetic measurement [35], fabric aesthetic prediction [36], and human facial aesthetic evaluation [37] through ANN. These studies have shown the ability of artificial intelligence to make decisions by imitating human vision and aesthetics.

The intelligent aesthetic assessment focuses on image recognition and classification problems. The research on the aesthetic perception of product form after nonlinear visual processing is insufficient, and it still stays in the stage of calculating product form beauty [38]. Based on human aesthetic preference and design aesthetics, Wong and Low [39] established a relationship between visual attention and visual aesthetics, and they improved the classification effect by extracting salient regional features. Based on Wong's extraction of salient features, Wang et al. [40] proposed an image aesthetic classifier through a machine learning method to evaluate image aesthetics. In addition, Zhang et al. [41] exploited the supervised learning method to obtain a judgment model to predict consumers' perceived aesthetics under the measurement of aesthetic principles. Because the aesthetic size of product form is affected by the subjective aesthetic of users, this prediction process is nonlinear and inconsistent. Thus, there is a tremendous technical difference between the product form and image aesthetic

prediction. The image aesthetic evaluation framework cannot be fully applied to the product form aesthetic evaluation.

Considering the guiding of consumers' perceptual cognition in the prediction of product aesthetic feeling, an ANN evaluation framework for visual aesthetics of product form is proposed according to the optical characteristics of product form from the perspective of consumers. Due to difficult data collection and insufficient samples in consumer perceptual cognition surveys, it is challenging to achieve high accuracy using traditional machine learning methods. To handle the problem, this article proposed a feature dimension compression method to improve the prediction accuracy of the training model. Finally, a high-precision perceptual model describing the relationship between designers and consumers is established to provide a valuable product design paradigm.

3. Methods Overview

Based on the related work introduced above, the obtained cognition is defuzzified. The results are used to establish a prediction model for measuring the aesthetic feeling of product form. The research route is shown in Figure 2.

3.1. Computation of Visual Cognitive Complexity

3.1.1. Cognitive Complexity. The DCC theory measures the complexity of a system from the perspective of functional requirements. It translates the complexity of the design

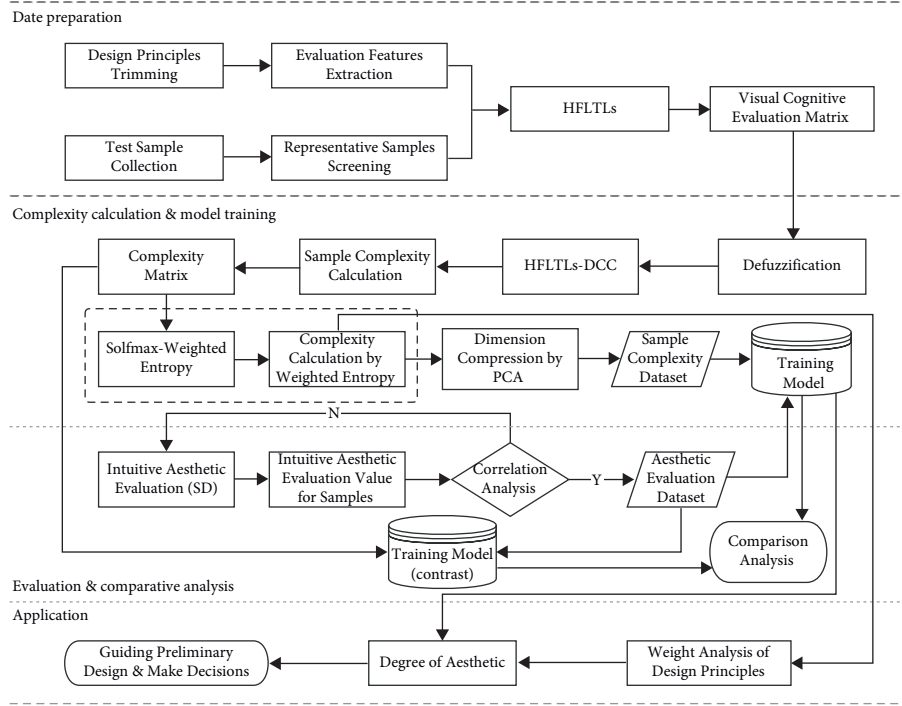


FIGURE 2: Research route of visual cognitive aesthetic prediction.

system into the probability of achieving functional requirements. It obtains the amount of complexity information that the product system conveys by calculating the conversion probability of emotional cognition. Therefore, according to the DCC theory, the complexity information of a user's visual cognition can be expressed as

$$I_p = -\log_2 p_s = \log_2 \left(\frac{1}{p_s} \right), \quad (1)$$

where p_s denotes the realization probability of cognitive field F_s . The higher the probability F_s , the lower the system complexity degree, and vice versa. Denoting the probability density function of the system as $P_x(eFR)$, the realization probability of the designing scope in a system F_s is formulated as follows:

$$p_s = \int_{dl}^{du} P_x(eFR) d(eFR). \quad (2)$$

In equation (2), du is the upper limit of the design range and dl is the lower limit of the design range. While in formula (1), I_p is the information quantity of product-cognitive system. The public scope is the overlapping area of the design-cognitive range and system-cognitive range. According to the principle of information axiom, equation (3) can be obtained, where A_{cr} is the area of the cognitive common range, R_{cc} is the cognitive common range, and R_{cs} is the cognitive system range.

$$p_s = \frac{R_{cc}}{R_{cs}} = A_{cr}. \quad (3)$$

The complexity of the design scheme can be evaluated by calculating the common area following the DCC theory.

Therefore, this study determines the complexity of the design system by calculating the public area and obtains the complexity of the product system after visual cognitive processing, as shown in Figure 3.

In Figure 3, the range of the system is the range of the actual cognitive system and the range of objective information, which is determined by the specific attributes of system. E-FR denotes the user's emotional needs, and it is a continuous variable. As the design goal, the design range represents the designer's demand for the design plan. The overlapping part of the design range and the system range is the public range, which means the ability of the design plan to meet the needs of the project. According to logical analysis, the larger the area of the public area, the lower the system complexity, and vice versa. Therefore, according to equation (3), the calculation formula for complexity can be expressed as

$$\mathcal{C} = \frac{R_{cc}}{R_{de} \cap R_{cc}}, \quad (4)$$

where R_{de} is the design range.

3.1.2. Hesitant-Fuzzy Information Axiom. According to the semantic level, the questionnaire is divided into specific grades (very low, low, average, high, very high) and corresponding scores (1, 2, 3, 4, 5). However, due to the fuzziness of cognition, there are fuzziness and hesitation in the process that users participate in the evaluation. For example, when the user evaluation score is 3, there may be two ranges of actual psychological perception: 2–3 or 3–4. The numerical scales cannot accurately reflect the user preferences, and it is not easy to calculate the information quantitatively.

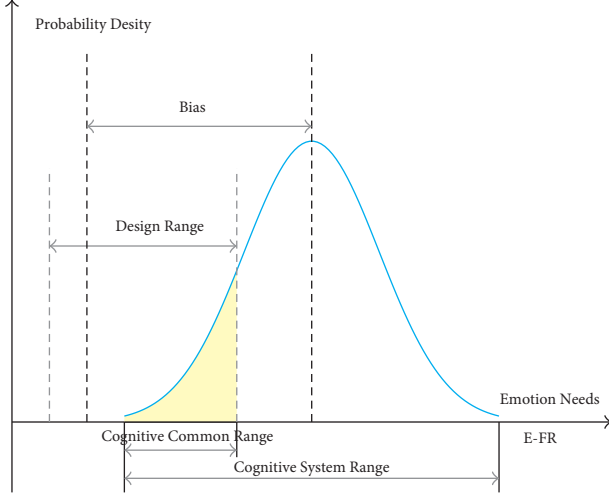


FIGURE 3: Schematic diagram of the cognitive common range and cognitive system range.

As can be seen, the product design system pays attention to the intuitive feelings of the objects in the evaluation process, which leads to the randomness of the evaluation results.

Therefore, the method of hesitant-fuzzy mathematics is introduced in the article. By defuzzifying the user evaluation with the hesitant-fuzzy linguistic term set [42], each scale obtained by the subject's score can be determined, and the different evaluation indicators of the sample can be calculated. Meanwhile, based on the information axiom design, the ability of each sample to meet different design requirements can be determined.

According to the theory of hesitant-fuzzy linguistic term set, let $A = \{A_1, A_2, \dots, A_n\}$ be an ordered language term set. The set contains odd language terms with symmetrical meanings. In this study, the language set is divided into five language terms: very low (VL), low (L), middle (M), high (H), and very high (VH), i.e., $A = \{A_1: VL, A_2: L, A_3: M, A_4: H, A_5: VH\}$. Given $A_\alpha, A_\beta, \lambda > 0$, there exist the following algorithms according to the literature [43]:

$$\begin{aligned} A_\alpha \oplus A_\beta &= A_{\alpha+\beta}, \\ \lambda A_\alpha &= A_{\lambda\alpha}, \\ (\lambda_1 + \lambda_2)A_\alpha &= \lambda_1 A_\alpha \oplus \lambda_2 A_\alpha, \\ \lambda(A_\alpha + A_\beta) &= \lambda A_\alpha \oplus \lambda A_\beta. \end{aligned} \quad (5)$$

In this study, the algorithms are extended to improve the accuracy of decision-making using concepts of set as follows:

Definition 1. Let $A = \{A_1, A_2, \dots, A_n\}$ be an ordered language term set, and $\mathbf{H}_s = \{h_s(x) | s \in \text{subset}(A), x \in X\}$ be a hesitant-fuzzy linguistic term set on domain X , which represents the set of all possible subordinate fuzzy language terms of an object.

Let $A = \{A_1: VL, A_2: L, A_3: M, A_4: H, A_5: VH\}$ be the fuzzy evaluation of product feature complexity. Then, $\mathbf{H}_s = \{h_s(1) = (A_2, A_3), h_s(2) = (A_3, A_4)\}$ of decision-maker's evaluation of two products complexity is a set of hesitant-fuzzy linguistic terms.

To evaluate different projects in the domain, an overall algorithm considering the evaluation of different decision makers is developed.

Definition 2. Suppose the hesitant-fuzzy linguistic term set $\mathbf{H}_s = \cup_{i=1}^n \mathbf{H}_s^i, i = [1, n]$ on domain X , and n is the number of decision makers. $\mathbf{H}_s^i = \{h_s^i(x) | s \in \text{subset}(A), x \in X, i \in [1, n]\}$ represents the hesitant-fuzzy linguistic evaluation of each decision-maker i . $A = \{A_1, A_2, \dots, A_n\}$ is the hesitant-fuzzy semantics, and the algorithm is defined as follows:

$$\begin{aligned} \mathbf{H}_s^i + \mathbf{H}_s^j &= \{h_s(x) | h_s^i(x) + h_s^j(x)\}, \\ \alpha \mathbf{H}_s^i &= \{h_s(x) | \alpha h_s^i(x)\}, \\ \alpha \mathbf{H}_s^i + \beta \mathbf{H}_s^j &= \{h_s(x) | \alpha h_s^i(x) + \beta h_s^j(x)\}, \end{aligned} \quad (6)$$

where the symbol \cup represents the sum of the number of ambiguous semantic elements. According to Definition 1, we have

$$\begin{aligned} \mathbf{H}_s &= \mathbf{H}_s^1 + \mathbf{H}_s^2, \\ \mathbf{H}_s^1 &= \{h_s(1) | (A_2, A_3)\}, \\ \mathbf{H}_s^2 &= \{h_s(1) | (A_3, A_4)\}. \end{aligned} \quad (7)$$

Therefore,

$$\mathbf{H}_s^1 + \mathbf{H}_s^2 = \{h_s(1) | (A_2, 2A_3, A_4)\}. \quad (8)$$

3.1.3. Defuzzification Calculation of Hesitation Fuzziness. According to Section 3.1.2, the user's hesitant-fuzzy evaluation matrix \mathbf{H}_s for product complexity can be obtained. In fuzzy control theory, the precise value transformation of fuzzy behavior is called antifuzzy. Since the evaluation matrix counts all possible evaluation sets, the defuzzification calculation is performed by seeking the expectation.

Definition 3. Suppose a fuzzy hesitation evaluation matrix \mathbf{A} that can be expressed as

$$\mathbf{H}_s = \mathbf{F}_s \odot \mathbf{A}. \quad (9)$$

The symbol \odot in equation (9) represents the product of two vectors by element position, and \mathbf{A} represents the hesitant-fuzzy linguistic term set matrix. Then, \mathbf{F}_s is the characteristic matrix of the fuzzy hesitant evaluation matrix \mathbf{H}_s , which represents the frequency of occurrence of the corresponding hesitant-fuzzy linguistic terms.

Denote the symbol $\text{deF}(X)$ as the defuzzification operation to solve the vector X . Then, according to Definition 3, we have

$$\begin{aligned} \text{deF}(\mathbf{H}_s) &= \text{deF}(\mathbf{F}_s \odot \mathbf{A}) \\ &= \frac{1}{s} \sum_{ies} \mathbf{F}_i. \end{aligned} \quad (10)$$

The formula shows that the defuzzification of \mathbf{H}_s is obtained by calculating the expectation of its eigenvector.

3.1.4. Complexity Calculation. The user's subjective evaluation is hesitant and vague. Therefore, by converting the personal evaluation into a hesitant-fuzzy semantic variable, the subjects' actual psychological potential evaluation value can be obtained more accurately. Through this method, the user's hesitant-fuzzy evaluation is transformed into hesitant-fuzzy semantics, and the membership function of hesitant-fuzzy semantics is obtained. According to the definition of the information axiom, the hesitant-fuzzy evaluation is exploited to transform the range of user emotional needs. Considering the characteristics of fuzzy mathematics, we can transform the design range into a trapezoidal area, as shown in Figure 4.

The hesitant-fuzzy value of the user's evaluation of product features can be obtained through the fuzzy hesitant language term set in equations (6) and (10). Assume that the hesitant-fuzzy score of the target is 3.26. Through this score, the hesitant-fuzzy complexity bounded can be obtained based on the information axiom, indicating the area of the shadow region in the figure. The fuzzy complexity is calculated according to different feature evaluations of the sample, and the feature complexity matrix of sample i is obtained by

$$C_i = [C_{i,1}, C_{i,2}, C_{i,3}, \dots, C_{i,n}], 1 \leq n \leq N. \quad (11)$$

The specific complexity calculation consists of the following steps:

- (1) Determine the complexity evaluation index.
- (2) Establish the hesitant-fuzzy cognitive matrix (HFCM) of the user evaluation.
- (3) Calculate the HFCM.
- (4) Normalize and calculate the complexity matrix of different features for all samples.

In Step 1, any element and color composition can trigger a psychological reaction after visual stimulation. The complexity of visual stimulation includes the number of elements and the degree of similarity and unity [44]. Design complexity is critical to the complexity of product form. It has always been the focus of research in the field of design. The principle of design complexity is defined by Gestalt psychology [45], visual complexity measurement [12], information reception [46], etc. It consists of design complexity [18], the quantity of objects, irregularity of objects, dissimilarity of objects, detail of objects, asymmetry of object arrangement, and irregularity of object arrangement. Through the analysis of the stimulus shape and the consumer language, the key components of the design complexity principle include the number of elements, the irregularity of object, the dissimilarity of object, the detail of object, the asymmetry of element arrangement, and the irregularity of element arrangement, which are taken as the characteristic induces of complexity, and described in Table 1.

In Step 2, the questionnaire is designed according to the six key components of the design complexity principles. The Likert scale is used to evaluate the sample complexity. The

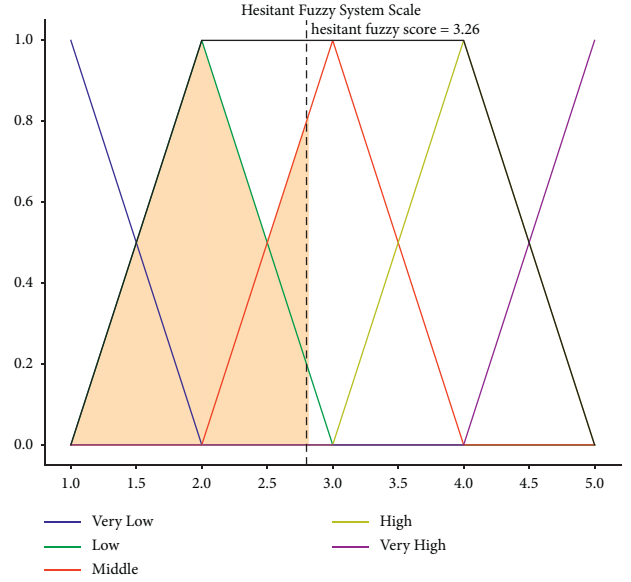


FIGURE 4: Hesitant-fuzzy common range diagram.

semantics of sample morphology are transformed into corresponding semantic variables according to the concept and complexity of the fuzzy linguistic term set. Meanwhile, the fuzzy value is used to express the evaluation value of the feature degree. The language term set of $S = \{S_1: VL, S_2: L, S_3: M, S_4: H, S_5: VH\}$ is used to evaluate the sensibility of the sample. In this way, the user's scoring matrix $S_k = [s_{ij}^k], i \in [1, M], j \in [1, N]$ for the complex features of sample k is obtained, where M is the number of subjects; N is the number of features, and K is the number of samples.

The characteristics of the complexity described above are denoted as: EN (Element Number), OI (Object Irregularity), OD (Object Dissimilarity), OT (Object deTail), AA (Arrangement Asymmetry), and AI (Arrangement Irregularity). Then, the matrix can be expressed as

$$S_k = \begin{matrix} \begin{array}{c|cccccc} \hline EN & OI & OD & OT & AA & AI \\ \hline \end{array} \\ \begin{array}{c} s_{11}^{(k)} & s_{12}^{(k)} & s_{13}^{(k)} & s_{14}^{(k)} & s_{15}^{(k)} & s_{16}^{(k)} \\ s_{21}^{(k)} & s_{22}^{(k)} & s_{23}^{(k)} & s_{24}^{(k)} & s_{25}^{(k)} & s_{26}^{(k)} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ s_{m1}^{(k)} & s_{m2}^{(k)} & s_{m3}^{(k)} & s_{m4}^{(k)} & s_{m5}^{(k)} & s_{m6}^{(k)} \end{array} \end{matrix}. \quad (12)$$

Each row represents a user's hesitant-fuzzy score on the sample in the matrix. S_k is the scoring matrix of a sample k by user m . $s_{mn}^{(k)}$ represents the intuitive evaluation of user m for feature n of sample k .

In Step 3, S_k is summed by column according to the hesitant-fuzzy linguistic calculation criterion expressed by equation (6). Then, the HFCM of feature n of the samples for the consumer is obtained:

$$R_n^{(k)} = \sum_{i=1}^m s_{in}^{(k)}. \quad (13)$$

Given the hesitant-fuzzy linguistic term set matrix $A = \{A_1, A_2, \dots, A_j\}$, the above formula can be expressed as

TABLE 1: Complexity induces and their evaluation principles.

Complexity index	Evaluation principles
Element Number	The number of main elements in product shape. It mainly refers to the number of constituent structures and components. When the shape contains more elements, the complexity is higher.
Object Irregularity	The overall product modeling has no regularity and order, does not have a unified coordination, and does not meet the Gestalt principle.
Object Dissimilarity	There is no similarity between the structural forms of product modeling (including modeling lines, lines and curves). The direction of the modeling line is not uniform and similar, and the product material and texture are not similar.
Object Detail	The degree of detail and decoration of the product. For example, decorative lines and decorative components, as well as the use of details and textures in product modeling design. When there are less details in product modeling, the complexity of design is greater.
Arrangement Asymmetry	The constituent elements (main functional components) of the product form an asymmetric arrangement. When there is no symmetrical design, the complexity is greater.
Arrangement Irregularity	The constituent elements (main functional components) of the product form an irregular arrangement and have no order lines. When the product space is randomly distributed, it has higher design complexity.

$$\mathbf{R}_{EN}^{(k)} = \mathbf{F}_{EN}^{(k)} \odot \mathbf{A}, \quad (14)$$

where the symbol \odot denotes the product of two vectors by element indices. Thus, an HFCM can be implied by \mathbf{F} , if \mathbf{A} is fixed.

Finally, in Step 4, $F_n^{(k)}$ is normalized, and its mean value is calculated according to the weight of the hesitant-fuzzy linguistic terms which affiliated.

$$M_n^{(k)} = \frac{\overline{F_n^{(k)}}}{\sum_{i=n}^m s_{i,n}^{(k)}} \cdot W^T = \frac{\sum_{i=n}^m (s_{i,n}^{(k)} * w_i)}{\sum_{i=n}^m s_{i,n}^{(k)}}. \quad (15)$$

Then the complexity degree $C_n^{(k)}$ of feature n for the sample is calculated following the method described in Section 3.1.3. The rest can be deduced by analogy. Based on this, the complexity degree matrix \mathbf{C}_N containing the complexity degree of all the features is obtained.

3.2. Exponential Weighted Entropy Complexity Calculation. After the user's cognitive complexity is calculated, there is noise in the data and should be eliminated according to the needs of neural network prediction. The entropy weight method determines the objective weight according to the index variability. This method has been widely used in engineering technology, social economy, and other fields. The smaller the information entropy of an index, the greater the dispersion of the index value and the more information it provides, so the more significant the weight in the comprehensive evaluation, and vice versa. To investigate the feature weights that affect the thorough evaluation of samples, an improved entropy weight model suitable for the data characteristics of this study is proposed.

Following the method described in Section 3.1.3, the fuzzy evaluation matrix $\mathbf{C}_N = [C_1, C_2, C_3, \dots, C_n]$, $1 \leq n \leq N$ of consumer hesitation is obtained. C_n is a column vector that represents the evaluation of different samples on feature n . The steps of feature weight calculation are as follows:

- (1) Use the maximum-minimization principle to normalize the evaluation matrix \mathbf{C}_n by column to obtain the normalized complexity matrix \mathbf{C}'_n :

$$\mathbf{C}'_N = \frac{\mathbf{C}_n - \min(\mathbf{C}_n)}{\max(\mathbf{C}_n) - \min(\mathbf{C}_n)} \Big|_{\text{column}}. \quad (16)$$

- (2) Calculate each feature's proportion of the features for the sample by column:

$$P_N = \frac{\mathbf{C}'_N}{\sum \mathbf{C}'_N} \Big|_{\text{column}}. \quad (17)$$

Thus, the weight matrix $P_{K \times N}$ with a dimension of $K \times N$ is obtained:

$$P_{K \times N} = |p_{ij}|, i \in [1, K], j \in [1, N]. \quad (18)$$

- (3) Based on the complexity matrix \mathbf{C}_N , the weight matrix $p_{i,j}$ of feature n of sample k can be obtained, and the entropy of each feature can be calculated:

$$e_j = -\frac{1}{\ln(n)} \sum_{i=1}^K p_{ij} \ln(p_{ij}), j \in [1, N]. \quad (19)$$

- (4) Use the exponential weight function to calculate the weight of e_j . The calculation is shown as follows:

$$w_j = \frac{e^{x_j}}{\sum_{j=1}^n e^{x_j}}. \quad (20)$$

In the formula, $\mathbf{x} = [x_1, x_2, \dots, x_n]$. Following this method, the values close to each other can be separated better, hence features with higher aesthetic impact can be screened out and higher prediction accuracy is obtained.

- (5) Finally, the weighted complexity of each sample is calculated by using the feature weights.

$$\mathbf{C} = \mathbf{W} \cdot \mathbf{C}_N. \quad (21)$$

Following the above steps, the sample complexity is calculated, where $\mathbf{W} = |w_j|, j \in [1, N]$.

3.3. Dimension Compression of Visual Cognitive Complexity. To guarantee the reliability of results, multi-dimensional information on research objectives is usually collected in

data analysis. Although there is a specific correlation between the dimensions, they cannot be analyzed independently. Otherwise, the research process will be affected by the loss of data information, leading to a bad deviation of conclusions. The PCA proposed by Turk and Pentlad [47] can solve the above problems. Based on K-L transformation (Karhunen-Loeve Transform), PCA projects data from high-dimensional space to low-dimensional space, saving the most critical K dimensions. These K dimensions with orthogonal characteristics are called principal components.

Since neural network training requires a large amount of data to achieve high accuracy, the amount of data will increase exponentially as the number of features increases. However, the samples in the test set are insufficient and difficult to collect. In this case, the amount of data is always small, resulting in the low accuracy of the training model. In this case, the PCA algorithm is adopted to reduce data dimension to train the neural network with a small amount of data. The specific steps are as follows:

- (1) Perform row-column conversion on the user complexity evaluation samples to generate matrix X with a dimension of $n \times m$, where n is the number of sample features, and m is the number of samples.
- (2) Normalize X with zero-mean operation.
- (3) Calculate the covariance matrix $1/nX^*(X^*)^T$ and eigenvectors of X^* by using the eigenvalue decomposition method (EVD) for singular matrix.
- (4) Rank the eigenvalues by size, the first values and the corresponding eigenvectors are selected to form the characteristic matrix P .
- (5) Map X to the new vector space based on P :

$$X' = PX, \quad (22)$$

where X' denotes the new data after dimension compression, and it makes up the training data set for the subsequent neural network.

3.4. Artificial Neural Network. Neural networks can solve complex problems without explicit models, which are used to investigate the relationship between product complexity and aesthetic degree and predict the aesthetic degree. As shown in Figure 5, an ANN contains multiple artificial neurons divided into the input, hidden, and output layers. Specifically, the input layer is responsible for receiving signals. The hidden layer is responsible for processing and integrating the received signals. Finally, the results are achieved in the output layer.

After the input passes through these layers, the regression or classification result can be obtained. The neural network continuously uses the training data for parameter adjustment. After training with a large number of data, the optimal weight of every neural is finally fitted. At this moment, the neural network achieves the best accuracy for data prediction. Since this study uses a small number of sample data, the over-fitting problem is easy to occur in the training process. We adopted the dropout technique in this

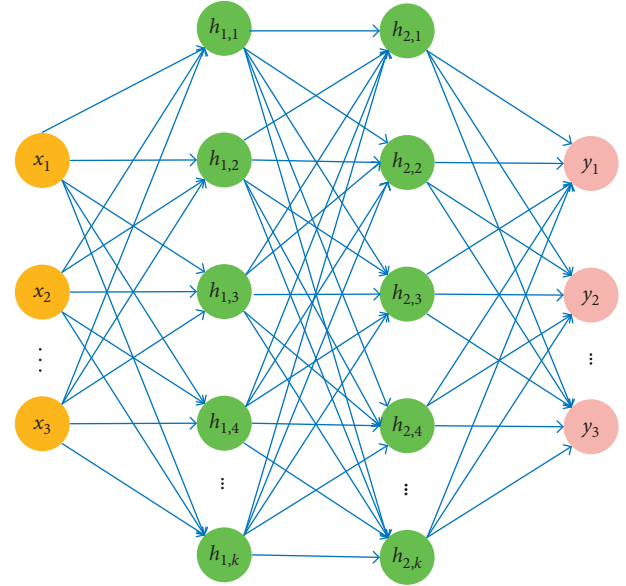


FIGURE 5: Artificial neural network structure.

study to handle this problem, and the method will be introduced below.


3.5. Establishing the Cognitive Space of Form Aesthetics. In order to obtain an accurate aesthetic evaluation of users, five-order SD method is adopted to launch the questionnaire. In our existing research [48], we summarized and sorted out the aesthetic principles in the product field, combining the modern product aesthetics research theory, and obtained 9 aesthetic principles preliminarily. According to the needs of this study, the 9 aesthetic principles are reduced by the fuzzy-delphi method (FDM), and finally top 6 principles that can most affect aesthetic evaluation are determined, i.e., unity (U), rhythm (r), simplicity (S), order (O), comfortable(C), and harmonize (H). Latter, the aesthetic evaluation is estimated using a linear weight method. For instance, assume the aesthetic evaluation of the i th subject about the j th sample is denoted by $\mathbf{A}_i^j = [U_i^j, R_i^j, S_i^j, O_i^j, C_i^j, H_i^j]$, where $i = 1, 2, \dots, m; j = 1, 2, \dots, n$. Thus the aesthetic evaluation of a sample can be expressed as

$$E_i^j = \frac{\sum_{n=1}^N \mathbf{A}_i^j}{N}, \quad (23)$$

where $N = 6$ denotes the number of principles (mentioned above) that are considered. Finally, a sample aesthetic evaluation matrix is obtained, which provides data support for neural network prediction.

4. Case Study

As a product that frequently interacts with people in life, the capsule coffee machine has a solid emotional connection with the public, which is more likely to arouse people's aesthetic resonance. Designers need to consider the structural level to provide users with emotional demand transformation. Therefore, the capsule coffee machine was



Sample

How long have you been using
Your capsule coffee machine?
_____/years

Element Number

1 2 3 4 5

Very Low Low Average High Very High

Object Irregularity

1 2 3 4 5

Very Low Low Average High Very High

Object Dissimilarity

1 2 3 4 5

Very Low Low Average High Very High

Object deTail

1 2 3 4 5

Very Low Low Average High Very High

Arrangement asymmetry

1 2 3 4 5

Very Low Low Average High Very High

Arrangement Irregularity

1 2 3 4 5

Very Low Low Average High Very High

FIGURE 6: Questionnaire format used in the research.

selected as the test sample for the visual cognition experiment. The experiment consists of the following steps.

4.1. Samples Collection. There are 2500 pictures collected through the Internet, home appliance market, newspapers, and magazines. Six hundred test pictures were obtained after preliminary screening, which process deletes the duplicate and vague ones. The experts screened 600 images and got 96 representative samples later, as shown in Appendix 5. This study mainly focuses on the shape of capsule coffee machines; thus, the influence of other dimensions on vision is eliminated. In the process of the subjects are screened, young subjects are preferred for the following reasons.

- (1) According to the regional culture and dietary habits, coffee audiences are concentrated in young customer groups.
- (2) Capsule coffee machine is a fashionable household product, which is widely used by young users.

At last, 30 questionnaires were collected, and the format is shown in Figure 6.

4.2. Data Preprocessing. Once the questionnaires were obtained, we screened the valid questionnaires according to the following criteria.

- (1) The participants had the experience of using capsule coffee machine.
- (2) No regular filling (70% of the answers are the same).
- (3) The questionnaire is complete without missing options.
- (4) The response time of the questionnaire is valid (the response time should be more than 10 minutes).

After eliminating the invalid questionnaires, we collected 23 valid questionnaires. The questionnaire recovery rate was 76.7%, which was in line with the recovery rate standard of the research questionnaire [49]. As a summary, the characteristics of valid questionnaire samples are shown in Table 2:

As can be seen, the summary characteristics of Table 2 are as follows.

- (1) The age of the respondents is mainly young, which meets the needs of the experiment.
- (2) In the samples, industrial design students and product designers are in the majority, who have good aesthetic knowledge.
- (3) The ratio of men to women is average.

4.3. Data Processing. This section exploited the hesitant-fuzzy information axiom to process the data. The complexity of consumers on different characteristics of the sample set was measured. Next, the feature complexity matrix was processed by the exponentially weighted entropy method described in Section 3.2 to obtain the complexity weights of different features. Meanwhile, the complexity evaluation result of the sample was obtained. Finally, the feature complexity matrix was analyzed by PCA to reduce the dimension of the data samples. The artificial neural network was constructed and trained with the data with a reduced size. In this way, the accuracy of the model was improved, and the impact of different characteristics on aesthetic evaluation was determined.

To illustrate the effectiveness of the proposed feature compression method, two data sets, raw data after PCA and raw data processed by the feature compression method above, are trained with ANN individually, comparison

TABLE 2: Statistics of valid questionnaire objects.

Feature	Option	Amount	Ratio (%)
Gender	Male	11	47.83
	Female	12	52.17
Age	18–25	8	34.78
	26–30	9	39.13
	31–40	6	26.09
Occupation	Business English	2	8.70
	Me Media	4	17.39
	Foreign Trade	2	8.70
	Student	5	21.74
	Product designer	3	13.04
	E-commerce salesperson	4	17.39
Using experience (year)	Manufacturing market personnel	3	13.04
	<0.5	4	17.39
	0.5–1	10	43.48
	1–2	4	17.39
	≥2	5	21.74

results of the convergence curve and the error curve are achieved at last.

4.4. Hesitant-Fuzzy Evaluation Matrix. All evaluation tables' feature domains and scoring domains were extracted separately, integrated, and processed. The obtained hesitant-fuzzy cognition matrix is shown in Table 3.

Each cell $C_{i,j}$ represents the hesitant-fuzzy score of the subject i for the sample j , and the order is EN, OI, OD, OT, AA, AI.

4.5. Visual Cognitive Complexity Calculation

(1) *Calculate the Fuzzy Evaluation Matrix and Analyze the Reliability.* Dehesitating fuzzy calculation is performed in Table 3 according to equation (10). The hesitant-fuzzy evaluation matrix $\hat{C}_{i,j}$ of user i on sample j is shown in Table 4.

The reliability of the evaluation matrix is analyzed, and the analysis results are listed in Table 5.

The results show that the evaluation is reliable and can be used for subsequent analysis.

(2) *Calculate the Complexity Matrix.* Firstly, the complexity of each feature of the sample is obtained by the quantization method described in Section 3.1.4. Take the complexity of the element of sample 1, i.e., $C_{EN}^{(1)}$, as an example. According to the questionnaires, $s_{11}^{(1)} = (A_2, A_3)$. The following result is obtained by summing by column.

$$\begin{aligned}
R_{EN}^{(1)} &= \sum_{i=1}^m s_{i1}^{(1)}, \\
&= (5A_1, 8A_2, 23A_3, 8A_4, 2A_5), \\
&= (5, 8, 23, 8, 2) \odot (A_1, A_2, A_3, A_4, A_5).
\end{aligned} \tag{24}$$

Thus, $F_{EN}^{(1)} = (5, 8, 23, 8, 2)$.

Then, $F_{EN}^{(1)}$ is normalized, and the mean value is calculated according to the weight of the fuzzy language terms which is affiliated.

$$\begin{aligned}
M_n^{(k)} &= \overline{F_n^{(k)}} \cdot W^T, \\
&= \frac{\sum_{i=1}^m (s_{i,n}^{(k)} * w_i)}{\sum_{i=1}^m s_{i,n}^{(k)}}, \\
&= [0.11, 0.17, 0.5, 0.17, 0.04] * [1, 2, 3, 4, 5]^T, \\
&= 2.8696.
\end{aligned} \tag{25}$$

Finally, the value of $C_{EN}^{(1)}$ is calculated following equation (14), and the result is 0.548771.

Similarly, the complexity matrix C_N of all subjects about each feature of all samples is calculated, where $N \in \{EN, OI, OD, OT, AA, AI\}$. The result is listed in Table 6.

(3) *Calculate the Characteristic Weight of the Complexity Matrix.* According to the complexity matrix C_N , the weight matrix P_{01} of the characteristic EN of sample 1 can be obtained and the entropy value of each feature is calculated according to equations (16)–(19), and the result is shown in Table 7.

The weight w_j of each feature is calculated by equation (20), and the calculation result is shown in Table 8.

According to the results in the table, the features EN, OI, OT, and O D have a high impact, and the weight of these four features accounts for more than 82% of the whole. Also, there is little difference in the weight of EN, OI, and OT features, so more design consideration should be paid to these three features in the early stage of product design.

(4) *Calculate the Complexity of the Test Sample.* According to the characteristic weight calculation shown in equation (21) and the weight vector w_j obtained in the last step, the

TABLE 3: Questionnaire hesitant-fuzzy cognitive matrix.

Subject	C_1	C_2	C_3	...	C_{96}
Sample	EN OI OD	EN OI OD	EN OI OD	...	EN OI OD
Features	OT AA AI	OT AA AI	OT AA AI	...	OT AA AI
1	{3, 4}{1, 2}{3, 4}	{2}{3, 4}{2, 3}	{3}{3, 4}{3, 4}	...	{2}{3, 4}{1, 2}
2	{3, 4}{1, 2}{3, 4}	{2}{3, 4}{2, 3}	{2}{2}{4}	...	{1}{2, 3}{1}
3	{3, 4}{1, 2}{3, 4}	{2}{3, 4}{2, 3}	{4}{3, 4}{2}	...	{4}{3, 4}{2}
4	{2}{1, 2}{3, 4}	{1, 2}{1, 2}{2, 3}	{3}{1, 2}{1, 2}	...	{3}{1, 2}{1, 2}
5	{1}{1}{1, 2}	{1}{1}{1, 2}	{2}{1}{2, 3}	...	{1, 2}{2, 3}{2, 3}
6	{1, 2}{1}{1}	{1}{1}{1}	{1, 2}{1}{1, 2}	...	{1, 2}{1}{1, 2}
7	{3, 4}{2}{3, 4}	{2}{2, 3}{3}	{2, 3}{3}	...	{4, 5}{2, 3}{4}
8	{4}{1, 2}{2}	{1, 2}{1, 2}{2}	{3, 4}{1, 2}{2, 3}	...	{3, 4}{2, 3}{3}
9	{3}{3}{3, 4}	{2, 3}{2, 3}{3}	{3, 4}{3}{3, 4}	...	{2}{2, 3}{2, 3}
10	{2, 3}{3, 4}{3}	{4, 5}{3, 4}{3}	{3, 4}{3, 4}{4}	...	{1, 2}{2, 3}{2, 3}
11	{1, 2}{2, 3}{3}	{1, 2}{3}{3}	{4, 5}{3}{2, 3}	...	{4, 5}{2, 3}{4}
12	{3, 4}{1, 2}{2, 3}	{2, 3}{2, 3}{3, 4}	{4, 5}{4, 5}{4}	...	{3, 4}{2, 3}{3}
13	{3, 4}{3}{2, 3}	{3, 4}{3}{3, 4}	{2, 3}{3}{4}	...	{4, 5}{4}{5}
14	{4}{3, 4}{4, 5}	{4}{4}{4}	{3, 4}{3, 4}{3, 4}	...	{5}{5}{5}
15	{2, 3}{2}{2}	{2}{1, 2}{1}	{4}{2, 3}{3}	...	{4, 5}{3, 4}{4, 5}
16	{2, 3}{2}{1, 2}	{1}{1}{1}	{3, 4}{3}{2}	...	{2}{2, 3}{2, 3}
...
23	{1, 2}{3, 4}{3, 4}	{2}{4}{3}	{1, 2}{4, 5}{3, 4}	...	{4, 5}{2, 3}{1, 2}
	{2}{2}{3, 4}	{1, 2}{4}{4}	{3, 4}{2, 3}{2}		{3}{2, 3}{1}

TABLE 4: Hesitant-fuzzy evaluation matrix.

Subject	C_1	C_2	C_3	...	C_{96}
Sample	EN OI OD	EN OI OD	EN OI OD	...	EN OI OD
Features	OT AA AI	OT AA AI	OT AA AI	...	OT AA AI
1	3.5 1.5 3.5	2 3.5 2.5	3 3.5 3.5	...	2 3.5 1.5
2	1 1.5 2.5	1.5 1.5 1	2 2 4	...	1.5 2.5 1
3	3.5 1.5 1 3.5	2 3.5 2.5	4 3.5 2	...	4 3.5 2
4	2 1.5 3.5	1.5 1.5 2.5	3 1.5 1.5	...	3 1.5 1.5
5	1 1 1.5	1 1 1.5	2 1 2.5	...	1.5 2.5 2.5
6	1.5 1 1	1 1 1	1.5 1 1.5	...	1.5 1 1.5
7	3.5 2 3.5	2 2.5 3	4.5 3 3	...	4.5 2.5 4
8	4 1.5 2	1.5 1.5 2	3.5 1.5 2.5	...	3.5 2.5 3
9	3 3 3.5	2.5 2.5 3	3.5 3 3.5	...	2 2.5 2.5
10	2.5 3.5 3	4.5 3.5 3	3.5 3.5 4	...	1.5 2.5 2.5
11	1.5 2.5 3	1.5 3 3	4.5 3 2.5	...	4.5 2.5 4
12	3.5 1.5 2.5	2.5 2.5 3.5	4.5 4.5 4	...	3.5 2.5 3
13	3.5 3 2.5	3.5 3 3.5	2.5 3 4	...	4.5 4 5
14	4 3.5 4.5	4 4 4	3.5 3.5 3.5	...	5 5 5
15	2.5 2 2	2 1.5 1	4 2.5 3	...	4.5 3.5 4.5
16	2.5 2 1.5	1 1 1	3.5 3 2	...	2 2.5 2.5
...
23	1.5 3.5 3.5	2 4 3	1.5 4.5 3.5	...	4.5 2.5 1.5
	2 2 3.5	1.5 4 4	3.5 2.5 2		3 2.5 1

TABLE 5: Reliability analysis.

Data set	Cronbach's Alpha	N of Items
Value	0.976	577

complexity degrees of every sample are obtained and listed in Table 9.

4.6. Dimension Reduction of Neural Network Data Set. This section introduces the use of the PCA algorithm described in Section 3.3 to perform data dimension reduction

on the sample complexity matrix in Table 6 and the hesitant-fuzzy evaluation matrix in Table 4. The MLE algorithm is adopted as the dimension reduction strategy [50]. In this way, more than 90% of data information is retained, and the data comparison after dimension reduction is shown in Table 10.

It can be seen that after PCA, the fuzzy evaluation matrix was compressed from the original six dimensions to five dimensions. However, the sample feature matrix of the complexity dimension can be compressed to two dimensions by the PCA algorithm. It provides the basis for neural network training with a small number of samples.

TABLE 6: Complexity degree matrix of samples.

Sample	Feature					
	EN	OI	OD	OT	AA	AI
0	0.548771	0.584216	0.609168	0.609168	0.856238	0.631096
1	0.808601	0.690832	0.663894	0.736484	0.709263	0.65
2	0.309168	0.517013	0.525236	0.396786	0.659074	0.556238
3	0.085066	0.359074	0.46673	0.090832	0.59707	0.491399
4	0.774764	0.743762	0.808601	0.817013	0.884216	0.76673
5	0.659074	0.67949	0.668904	0.645558	0.83327	0.690832
6	0.422495	0.422495	0.563516	0.517013	0.791399	0.67949
7	0.563516	0.491399	0.517013	0.556238	0.659074	0.577505
8	0.374102	0.443762	0.409263	0.436484	0.668904	0.451229
9	0.640926	0.62051	0.636106	0.65	0.715784	0.67949
10	0.35	0.636106	0.59707	0.458885	0.743762	0.663894
11	0.65	0.548771	0.548771	0.685066	0.674102	0.659074
12	0.690832	0.736484	0.696786	0.584216	0.89707	0.76673
13	0.2	0.07949	0.085066	0.241115	0.309168	0.225236
14	0.609168	0.32051	0.35	0.584216	0.614934	0.436484
15	0.090832	0.129395	0.129395	0.143762	0.136484	0.109263
16	0.491399	0.62051	0.508601	0.659074	0.668904	0.696786
...
96	0.685066	0.396786	0.436483	0.679489	0.614933	0.570604

TABLE 7: Complexity entropy of all features.

Feature	EN	OI	OD	OT	AA	AI
Entropy	0.972781574	0.975170034	0.982771291	0.97592165	0.991663718	0.986672343

TABLE 8: Weights of complexity features.

Feature	EN	OI	OD	OT	AA	AI
Value	0.236642	0.215876	0.14979	0.209342	0.072477	0.115873

TABLE 9: Complexity degree of samples.

Sample	0	1	2	3	...	95
Complexity Degree	3.70047259	4.145274102	3.024196597	2.170415879	...	3.383364839

TABLE 10: Data comparison after dimensions reduction.

Complexity after PCA		Fuzzy evaluation after PCA				
-0.518189663	-0.143490398	-0.614935017	0.633710287	-0.19771885	1.271722184	0.398531806
-1.094645356	1.40387409	-0.318278935	0.058520731	-0.302739578	1.338663212	0.894113214
0.274974012	-1.610609189	-1.999036566	0.229851835	0.290905989	-0.783309149	-0.484946857
1.283635824	-2.645106506	-0.080670741	-0.698590835	0.0236130354	-1.563307116	0.790976881
-1.698758004	0.434116341	-0.226322347	0.893042526	0.82571295	-0.078573414	0.250567461
-0.95385099	-0.172855553	0.118505627	-0.476348782	0.097839099	-2.515771325	0.132640173
0.077341782	-0.729233594	0.985001623	0.941788653	0.733555137	-1.681957829	-0.577861592
-0.295554003	0.243283864	-0.882831548	-0.489674961	0.243473972	1.344637579	0.256531062
0.457412258	0.132047054	-0.333163115	-0.49255516	-1.929329737	0.976861669	0.061394976
...
-0.215180898	2.107231765	-0.237435125	0.287610777	-2.113607129	-1.986364692	-1.446246687

4.7. *Product Aesthetics Prediction Model Construction.* This section constructed an aesthetic prediction neural network learning model, as shown in Figure 5(b). The

number of input nodes is N , which indicates the effective feature number of input samples. Meanwhile, the number of hidden layers is two, and the number of output layer nodes is

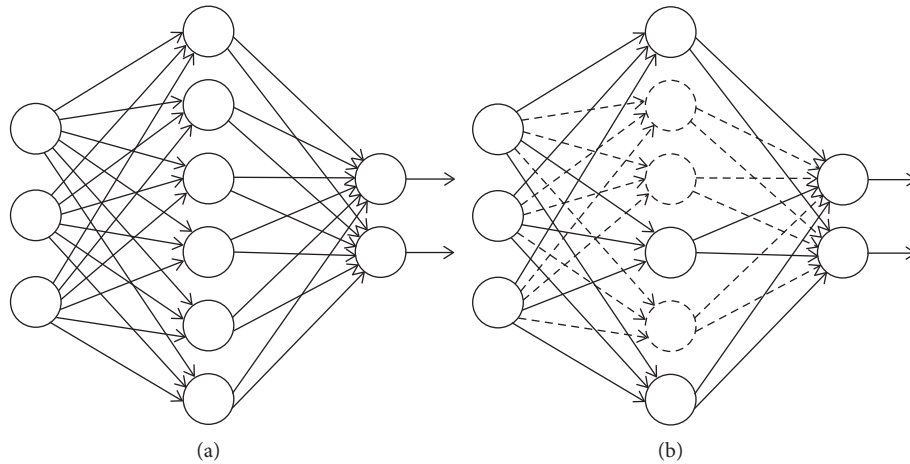


FIGURE 7: Structures of ANN with/without dropout. (a) ANN without dropout. (b) ANN without dropout.

five, meaning different subjective aesthetic evaluation values. The aesthetic evaluation is regarded as the label of training data, which is achieved according to the method discussed in Section 3.5.

It is considered that the increase in the number of nodes in the output layer will lead to a high error of the neural network trained by a small number of samples. In this case, the aesthetic score of this questionnaire adopted the fifth-order Likert scale without hesitation, so its score can be directly used as the label of model training without antihésitation.

The over-fitting problem in the training process will decrease the prediction accuracy of the trained model on the test data. The dropout technique was exploited to avoid over-fitting, and its principle is described as follows.

Figure 7(a) displays an ANN without regularization, which is susceptible to over-fitting. In the figure, the solid arrows linking the front and rear nodes imply no loss when the data is delivered from the upper layer to the lower layer. The ANN illustrated in Figure 7(b) consists of several dashed nodes. These indicate that some nodes are stochastically inactive in back-propagation and forward propagation. These nodes do not participate in the training of ANN. There are several advantages.

- (1) The training effect is smoothed. The random deviation generated in the training process of ANN can be utilized to equalize the training parameters, which leads to a more accurate ANN model.
- (2) Neuronal coupling is reduced. Since dropout makes a neuronal not always active in the recursive training of an ANN, the updating of weights no longer depends on the interaction of hidden nodes with fixed relationships. In this case, the situations where some features are compelling only if other certain features are activated are decreased.
- (3) Like the basic idea of genetic algorithm, the species tend to adapt to the environment to survive. Environmental mutations can make it difficult for the species to respond in time. The emergence of gender can reproduce varieties that adapt to the new

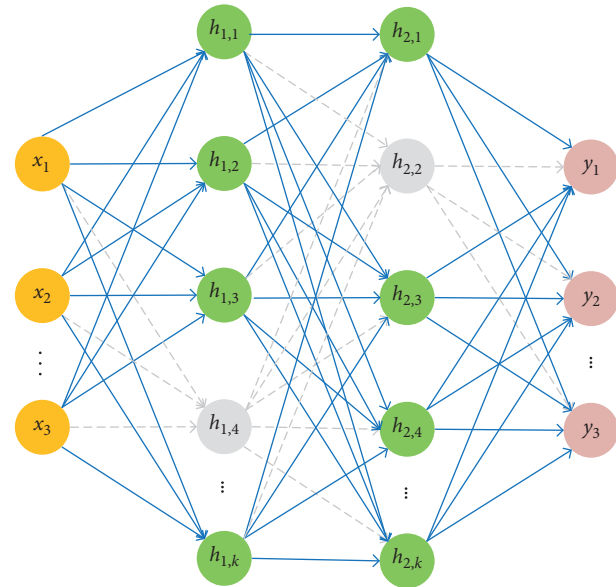


FIGURE 8: Dropout ANN used in the article.

environment, thus effectively preventing over-fitting and avoiding species extinction when the environment changes.

Therefore, the dropout layer with a failure probability of 20% was adopted in this study. During each propagation, 20% of the nodes in the hidden layer will fail. It cannot update parameters to the back layer until the subsequent propagation begins. The final neural network structure is shown in Figure 8.

Here, $h_{1,4}$ and $h_{2,2}$ denote the nodes dropped in propagation. Dashed lines denote the connections between the nodes, and their weights are set to 0 to disable the updating of ANN parameters in this propagating process.

The number of nodes in the input layers varies according to different training methods. In this study, the dimensions of input data are two and five, as Table 10 shows. According to the principles listed in [51], the number of nodes in hidden layers should satisfy the requirement as given below:

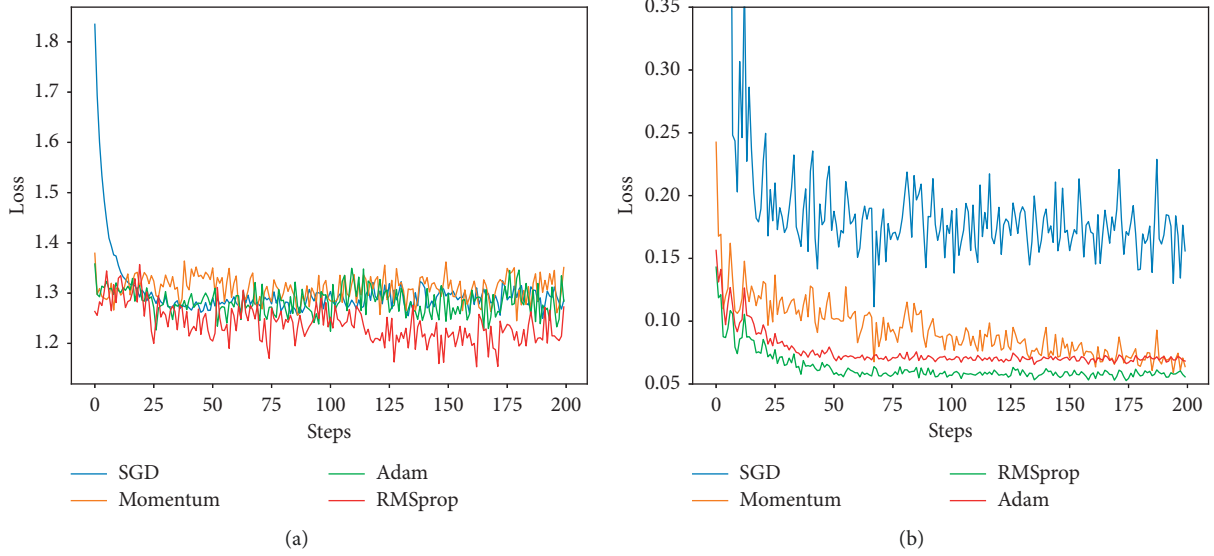


FIGURE 9: Performance comparison of the two models. (a) Loss of training with original data after PCA. (b) Loss of training with complexity degree after PCA.

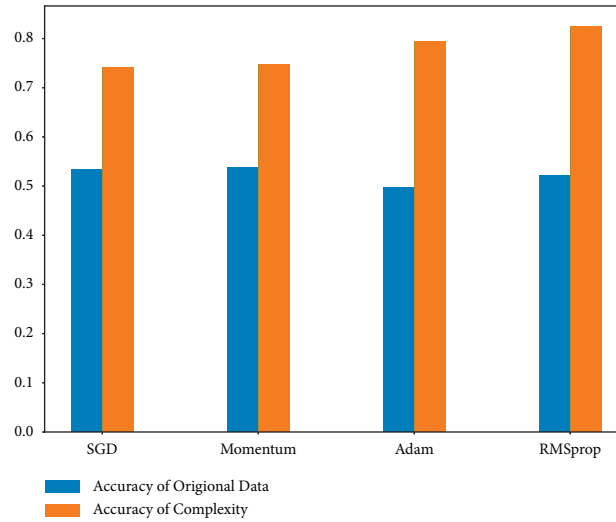


FIGURE 10: Accuracy achieved for different optimizers.

$$N_h \geq (N_{in} + N_{out}) * \frac{2}{3}. \quad (26)$$

Therefore, N_h was constrained to ensure the stability of the neural network structure during training process.

$$N_{in} = \max(N_i), N_i \in \text{set}(N), \quad (27)$$

where N denotes all the possible dimensions of the data input. In this study, N_{in} is 8. It is enough for training the ANN because a too large or too small value will lead to bad performance. According to the scoring categories, it is obvious that the number of nodes of the output layer should be set to 5.

To evaluate the effectiveness of the dimension compression method proposed, we took several different optimizers for comparison, including stochastic gradient descent

(SGD) optimizer, random gradient descent optimizer with momentum (MSGD), and Adam optimizer and RMSProp optimizer, in this article. For brevity, the principles of these optimizers are not introduced here. The training process consists of 200 epochs. Meanwhile, the selected data samples are shuffled and divided into the training set and test set at a ratio of 7:3. Six sets of data are read for batch training in each epoch. Eventually, the trained model is evaluated on the test sets to analyze its accuracy. The convergence characteristics of the loss function and the mean-square error (MSE) and the model prediction accuracy are provided in Figure 9.

It can be seen from Figure 9 that the ANN tends to converge after 50 epochs, and the loss function did not decline due to the small number of samples. However, a great improvement in performance has been obtained.



FIGURE 11: Samples list in order of complexity.

In Figure 10, the blue and orange histograms, respectively, represent the accuracy of ANN trained on the original data and the complexity with dimension reduction by PCA.

The result indicates that the proposed method can effectively compress the data dimension and significantly improve the prediction accuracy of the ANN. The samples sorted by

complexity from low to high are shown in Figure 11. As can be seen, the results conform to people's subjective aesthetics to a certain degree.

5. Conclusion

Design activities tend to express designers' emotions, and design management pursues rational benefits. Correct design decisions can directly improve product design's success rate and increase enterprise benefits in design management. Therefore, the design decision is critical in design management. In this process, technical design decisions depend on the construction of mathematical and morphological models. The mathematical model of design decision-making usually studies the relationship between various factors in the decision-making object. It establishes a consumer aesthetic factor model and assists in evaluating the design scheme and the smooth implementation of product development in design management. This study uses a mathematical model to measure the complexity of users' visual cognition and establish the objective analysis and prediction of product aesthetic factors, which can guide product strategic decision-making and provide design innovation ideas for enterprise design management. The proposed method can help the design management evaluate the aesthetic feeling of the decision-making object through a quantitative questionnaire survey (the questionnaire is shown in the Figure 6).

Thus, it grasps the product's strategic decision in advance. Aiming at the problem that perceptual data are small and challenging to collect, we propose a machine learning model for small sample prediction, combined with perceptual engineering theory. The results show that the proposed model in this article can effectively improve the prediction accuracy and help designers quickly and conveniently obtain the design factors that affect the aesthetic feeling of decision-making objects in design management and the time and workforce consumption caused by surveys and interviews can be reduced. Effective design decision-making is the key to improving design management. Our method can help designers develop products with high user satisfaction to the greatest extent and help enterprises achieve the goal of gaining more substantial competitiveness.

The approach proposed in this article can be used for the intelligent aided design of product aesthetic evaluation by measuring product visual cognitive complexity. However, there left a few limitations. On the one hand, this article mainly focuses on complexity quantification and aesthetic prediction methods. Thus the shape of the product is not taken into consideration. Although it provides design decision-making thinking for design management, there is no more profound and systematic discussion of specific measures at the management level. Therefore, we will conduct a more comprehensive study on criteria based on this study in future research. On the other hand, this article adopts the control variable method to study the shape and visual cognition, eliminating variables such as color, material, and touch. However, it should be noted that these variables also

impact the beauty of products. Therefore, these variables need to be further studied in the following work and the impact on different cultures and regions.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

Acknowledgments

This work was supported by Shanghai Philosophy and Social Fund Project (Grant no. 2019EWY010).

References

- [1] S. Lakkhal, A. Darmon, J. P. Bouchaud, and M. Benzaquen, "Beauty and structural complexity," 2019, <https://arxiv.org/abs/1910.06088>.
- [2] R. C. Wilson, A. Shenhav, M. Straccia, and J. D. Cohen, "The eighty five percent rule for optimal learning," *Nature Communications*, vol. 10, no. 1, p. 4646, 2019.
- [3] H. Leder and M. Nadal, "Ten years of a model of aesthetic appreciation and aesthetic judgments: the aesthetic episode – developments and challenges in empirical aesthetics," *British Journal of Psychology*, vol. 105, no. 4, 2014.
- [4] C. M. Hagerhall, T. Purcell, and R. Taylor, "Fractal dimension of landscape silhouette outlines as a predictor of landscape preference," *Journal of Environmental Psychology*, vol. 24, no. 2, pp. 247–255, 2004.
- [5] S. U. Jian-Ning, L. I. Ming, A. M. Zhou, and S. T. Zhang, "Aesthetic measure evaluation model of product morphology and its application," *Journal of Lanzhou University of Technology*, 2018.
- [6] P. Zhang and Y. Luo, "Study on complex systems from the perspective of design centric complexity," *Journal of Machine Design*, 2020.
- [7] J. Delin, S. Sharoff, S. Lillford, and C. Barnes, "Linguistic support for concept selection decisions," *Artificial Intelligence for Engineering Design, Analysis and Manufacturing*, vol. 21, no. 02, pp. 123–135, 2007.
- [8] N. P. Suh, "Complexity in engineering," *CIRP Annals*, vol. 54, no. 2, pp. 46–63, 2005.
- [9] N. P. Suh, *Complexity: Theory and Applications*, Oxford University Press, Oxford, UK, 2005.
- [10] S. Lloyd, "Measures of complexity: a nonexhaustive list," *IEEE Control Systems Magazine*, vol. 21, no. 4, 2001.
- [11] A. Newell and J. C. Shaw, *Human Problem Solving*, 1972.
- [12] D. C. Donderi, "Visual complexity: a review," *Psychological Bulletin*, vol. 132, no. 1, pp. 73–97, 2006.
- [13] J. Rigau, M. Feixas, and M. Sbert, "An information-theoretic framework for image complexity," in *Proceedings of the Computational Aesthetics 2005: Eurographics Workshop on Computational Aesthetics in Graphics, Visualization and Imaging 2005*, Girona, Spain, May 2005.
- [14] A. Oliva, M. L. Mack, and M. Shrestha, "Identifying the perceptual dimensions of visual complexity of scenes," *Proc*

- Annual Meeting of the Cognitive Science Society*, vol. 3, no. 49, pp. 1041–1046, 2004.
- [15] D. E. Berlyne and T. F. Maher, “Verbal and exploratory responses to visual patterns varying in uncertainty and in redundancy,” *Studies in the new experimental aesthetics: Steps Toward an Objective Psychology of Aesthetic Appreciation*, vol. 10, no. 1, 1974.
- [16] M. Baxter, *Product Design: A Practical Guide to Systematic Methods of New Product Development*, 1995.
- [17] X. Gao, L. Wen, D. Tao, and X. Li, “Image quality assessment and human visual system,” *Proc of the Visua*, vol. 7744, no. 5, pp. 17–19, 2010.
- [18] R. Pieters, M. Wedel, and R. Batra, “The stopping power of advertising: measures and effects of visual complexity,” *Journal of Marketing*, vol. 74, no. 5, 2010.
- [19] L. Sun, T. Yamasaki, and K. Aizawa, “Relationship between visual complexity and aesthetics: application to beauty prediction of photos,” in *Proceedings of the Workshop at the European Conference on Computer Vision*, Zurich, Switzerland, September 2014.
- [20] L. A. Zadeh, “Fuzzy algorithms,” *Information and Control*, vol. 12, no. 2, pp. 94–102, 1968.
- [21] H. C. Wu, “Linear regression analysis for fuzzy input and output data using the extension principle,” *Computers & Mathematics with Applications*, vol. 45, no. 12, pp. 1849–1859, 2003.
- [22] L. H. Chen, W. C. Ko, and F. T. Yeh, “Approach based on fuzzy goal programming and quality function deployment for new product planning,” *European Journal of Operational Research*, vol. 259, no. 2, 2017.
- [23] H. Liu, “An integrated fuzzy decision approach for product design and evaluation,” *Journal of Intelligent and Fuzzy Systems: Applications in Engineering and Technology*, vol. 25, no. 3, 2013.
- [24] J. Hirokawa, A. Vaughan, P. Masset, T. Ott, and A. Kepecs, “Frontal cortex neuron types categorically encode single decision variables,” *Nature*, vol. 576, pp. 446–451, 2019.
- [25] O. Kulak and C. Kahraman, “Fuzzy multi-attribute selection among transportation companies using axiomatic design and analytic hierarchy process - sciencedirect,” *Information Sciences*, vol. 170, no. 2–4, pp. 191–210, 2005.
- [26] H. C. Shen and K. C. Wang, “Affective product form design using fuzzy kansei engineering and creativity,” *Journal of Ambient Intelligence and Humanized Computing*, vol. 7, no. 6, pp. 875–888, 2016.
- [27] S. Chanyachatchawan, H. B. Yan, S. Sriboonchitta, and H. Van Nam, “A linguistic representation based approach to modelling kansei data and its application to consumer-oriented evaluation of traditional products,” *Knowledge-Based Systems*, 2017.
- [28] Y. Yang, “Kansei evaluation method of product form design based on hesitant fuzzy linguistic term sets and particle swarm optimization,” *Journal of graphics*, 2021.
- [29] L. Wang and C. Zhao, “The expert synthesis and integration research method based on hesitant fuzzy language,” *Systems Engineering-Theory & Practice*, 2021.
- [30] H. Liao, Z. Xu, and X.-J. Zeng, “Hesitant fuzzy linguistic vikor method and its application in qualitative multiple criteria decision making,” *IEEE Transactions on Fuzzy Systems*, vol. 23, no. 5, pp. 1343–1355, 2015.
- [31] I. Beg and T. Rashid, “Topsis for hesitant fuzzy linguistic term sets,” *International Journal of Intelligent Systems*, vol. 28, no. 12, 2013.
- [32] R. M. Rodriguez, L. Martinez, and F. Herrera, “Hesitant fuzzy linguistic term sets for decision making,” *IEEE Transactions on Fuzzy Systems*, vol. 20, no. 1, pp. 109–119, 2012.
- [33] F. P. Ava, “A large-scale database for aesthetic visual analysis,” in *Proceedings of the IEEE Conference on Computer Vision & Pattern Recognition*, Providence, RI, USA, June 2012.
- [34] Y. Kao, K. Huang, and S. Maybank, “Hierarchical aesthetic quality assessment using deep convolutional neural networks,” *Signal Processing: Image Communication*, vol. 47, pp. 500–510, 2016.
- [35] Y.-C. Lin, C.-H. Yeh, and C.-C. Wei, “How will the use of graphics affect visual aesthetics? a user-centered approach for web page design,” *International Journal of Human-Computer Studies*, vol. 71, no. 3, pp. 217–227, 2013.
- [36] B. K. Behera and R. Mishra, “Artificial neural network-based prediction of aesthetic and functional properties of worsted suiting fabrics,” *International Journal of Clothing Science & Technology*, vol. 19, no. 5, 2007.
- [37] M. Xu, F. Chen, L. Lu et al., “Bio-inspired deep attribute learning towards facial aesthetic prediction,” *IEEE Transactions on Affective Computing*, vol. 12, no. 1, 2018.
- [38] A. Zhou, S. U. Jianning, S. Yan, J. Ouyang, and S. Zhang, “Product multi-image prediction model based on aesthetic measure of form,” *Journal of Graphics*.
- [39] L. K. Wong and K. L. Low, “Saliency-enhanced image aesthetics class prediction,” in *Proceedings of the IEEE International Conference on Image Processing*, Cairo, November 2009.
- [40] W. N. Wang, L. Wang, M. Q. Zhao, C. J. Cai, and X. M. Xu, “Image aesthetic classification using parallel deep convolutional neural networks,” *Acta Automatica Sinica*, 2016.
- [41] J. Zhang, J. Yu, K. Zhang, X. S. Zheng, and J. Zhang, “Computational aesthetic evaluation of logos,” *ACM Transactions on Applied Perception*, vol. 14, no. 3, 2017.
- [42] V. Torra, “Hesitant fuzzy sets,” *International Journal of Intelligent Systems*, vol. 25, no. 6, pp. 529–539, 2010.
- [43] Y. Dai, Z. Xu, L. Yan, and Q. Da, “New evaluation scale of linguistic information and its application,” *Chinese Journal of Management Science*, 2008.
- [44] G. L. Geissler, G. M. Zinkhan, and R. T. Watson, “The influence of home page complexity on consumer attention, attitudes, and purchase intent,” *Journal of Advertising*, vol. 35, no. 2, 2013.
- [45] M. L. Simmel and R. Arnheim, “Art and visual perception: a psychology of the creative eye,” *American Journal of Psychology*, vol. 68, no. 2, 1955.
- [46] F. Attneave and Fred, “Some informational aspects of visual perception,” *Psychological Review*, vol. 61, no. 3, pp. 183–193, 1954.
- [47] M. Turk and A. Pentland, “Eigenfaces for recognition,” *Journal of Cognitive Neuroscience*, vol. 3, 1991.
- [48] X. Wu, M. Yang, and Z. Su, “Pleasurable emotions of product design,” in *Proceedings of the IHSI 2021 Conference*, Palermo, Italy, February 2021.
- [49] E. R. Babbie, “The practice of social research,” *Contemporary Sociology*, vol. 5, no. 2, 1976.
- [50] T. P. Minka, “Automatic choice of dimensionality for pca,” , <https://tminka.github.io/papers/pca/>, 2001.
- [51] S. W. Hsiao and H. C. Huang, “A neural network based approach for product form design,” *Design Studies*, vol. 23, no. 1, pp. 67–84, 2002.