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# Research on the association mechanism and evaluation model between fNIRS data and aesthetic quality in product aesthetic quality evaluation

Yong Wang, *Member, IEEE*, Fanghao Song, Yan Liu, Yaying Li, *Member, IEEE*, Weihao Wang, Qiqi Huang, Yang Hu

## I. INTRODUCTION

**Abstract**—Aesthetic quality evaluation has been an important research question in the field of user experience in product design. However, the feasibility and accuracy of using fNIRS data for product aesthetic quality evaluation are unknown. In this paper, we analyze the correlation and association between fNIRS data and aesthetic quality and designed a product aesthetic quality evaluation model to answer this question. We find that HBO<sub>2</sub> data in the prefrontal (S19-D11), frontal (S4-D3), temporal (S3-D1), and parietal (S8-D8) regions of the brain have significant correlations and logistic relationships with high visual product aesthetic quality, whereas HBO<sub>2</sub> data in the prefrontal (S19-D11) and parietal (S8-D8) regions of the brain have significant correlations and association relationships. These data can be used for products aesthetic quality evaluation. Importantly, the overall prediction accuracy of the model to evaluate products' aesthetic quality is 84.1%. The model is therefore able to better distinguish and evaluate the aesthetic quality of products. This study demonstrates the feasibility of using fNIRS data to evaluate the aesthetic quality of products and shows that the product aesthetic quality evaluation model can provide an objective and accurate decision-making reference to help designers evaluate and improve the aesthetic quality of products.

**Index Terms**—Affective computing, product design, user experience, aesthetic computing, aesthetic quality evaluation, machine learning, functional near-infrared spectroscopy (fNIRS)

What is the sense of aesthetic? An aesthetic sense is the human feeling evoked by the forms of harmony, order, and the beauty of things [1], [2]. In the field of product design research, aesthetics is a crucial factor that influences product success, user purchase intent, user satisfaction and consumer behavior [3], [4]. In fact, the positive impact of product aesthetics even extends to perceived usability [2], trust and credibility [5] and brand loyalty [6]. Aesthetic quality evaluation influences choices in important areas of human activity, including mate choice, consumer behavior, artistic appreciation and moral judgment [7]. The evaluation of product aesthetic quality is a key step for engineers and designers to create products with high visual aesthetic quality, and the results of product aesthetic quality evaluation affect the final quality of the product and the success rate of the product [8], [9]. Therefore, product aesthetic quality has received increasing attention from researchers in the fields of affective computing, product design, and user experience.

To date, researchers have attempted to evaluate the aesthetic quality of products using various methods. Two research paradigms are included in the study of product aesthetic evaluation: subjective evaluation and objective evaluation [10], [11]. Subjective evaluation is studied in accordance with the theory proposed by Kant, which states that “the feeling of aesthetic produced by human beings is the key to the explanation of aesthetic”, while objective evaluation is studied in accordance with the theory proposed by Plato, which states that “the properties of aesthetic are to be found in the attributes and forms of objective things” [12], [13]. Subjective evaluation in particular is considered to be a useful and widely adopted method [14].

Product aesthetic quality can elicit emotional generation and evaluative responses in humans [7]. Functional near-infrared spectroscopy (fNIRS) can capture the subtle brain activity of a subject during evaluation, providing a new and objective means of evaluating the aesthetic quality of products [15]. Scholars have explored changes in subjects' brains when they are faced with various stimuli (e.g., paintings, faces, and advertisements) by capturing data such as oxygen and hemoglobin (HBO<sub>2</sub>) and deoxygenated hemoglobin (HBR) through fNIRS. These studies found that aesthetic quality was significantly correlated with fNIRS data, which can be used to

- Y. Wang, F. H. Song, Y. Liu, Y. Y. Li, W. H. Wang, Y. Hu are with the Institute of Industrial Design, School of Mechanical Engineering, Shandong University, Jinan 250061, China. E-mail: {Yong Wang}201920443@mail.sdu.edu.cn, {Fanghao Song}songfanghao@sdu.edu.cn, {Yan Liu}liuyan2008@sdu.edu.cn, {Yaying Li}lilianayy@163.com, {Weihao Wang}201934061@mail.sdu.edu.cn, {Yang Hu}201934061@mail.sdu.edu.cn, 202214463@mail.sdu.edu.cn.
- Q. Q. Huang, is with the School of Computer Science and Informatics, Cardiff University, Parke Place, Cardiff, Wales, UK. E-mail: {Qi Qi Huang}sduhuangqiqi@163.com.
- (Corresponding author: Fanghao Song, and Yan Liu).

evaluate different aesthetic qualities [7], [16], [17], [18].

However, the use of functional near-infrared brain imaging for aesthetic quality evaluation in the context of product design has not been fully explored. On the one hand, it is unknown whether fNIRS data can be used for product aesthetic quality evaluation. The direct application of existing research findings on stimulus materials, such as paintings and faces, to the evaluation of aesthetic qualities in product design may be risky [19]. Different types of stimulus materials may induce different emotional changes, and directly using research from other fields to explain product aesthetics simplifies the problem [20]. On the other hand, the accuracy of the product aesthetic quality evaluation model based on fNIRS data is unknown due to the lack of associations between fNIRS data and product aesthetic quality [21]. The fNIRS collection technique, like any technique or method, does not reveal anything directly. Therefore, the lack of a theoretical model of the association between product aesthetic quality and fNIRS data can lead to a loss of explanatory power [14], [22].

Addressing the feasibility and accuracy of fNIRS data for the evaluation of product aesthetic quality has become an issue worthy of consideration [23]. To solve the above problems, we chose product images as stimulus materials, defined the aesthetic quality of product images, and applied the correlation function of SPSS Statistics 26 software to analyze the correlation between the fNIRS data and the aesthetic quality of the products of 50 subjects to answer the question of whether fNIRS physiological data can be used for the evaluation of aesthetic quality. We also applied the multivariate logistic (M) algorithm in machine learning to explore and analyze the correlation between the fNIRS data and the aesthetic quality of different products. Furthermore, we propose for the first time a model for evaluating the aesthetic quality of products based on fNIRS data and the results of the multivariate logistic (M), which plays an important role in improving the accuracy of evaluation of product aesthetics. In addition, we verified the validity of the product aesthetic quality evaluation model and the aesthetic quality of the experimental materials with fNIRS data and subjective data from other subjects. This is an important innovation to the existing theory of product aesthetic quality evaluation and an extension of the application of fNIRS data and the application of the multivariate logistic (M) algorithm.

The rest of the paper is organized as follows. Section 2 is the literature review of related work, and Section 3 is the methodology and experimental protocol. Section 4 presents the findings of the paper. Section 5 presents the discussion of the paper. The last section provides a summary and future directions.

## II. RELATED WORK

### 2.1 Aesthetics and product aesthetic quality

Within product design research, scholars describe a product's aesthetic quality as a human sensation brought about by visual forms of harmony, order and beauty [2], [8]. Beauty

can be perceived through sight, sound, touch, smell and taste [24].

Product aesthetic quality is crucial for product design [5]. In a competitive market, companies are shifting their attention to the emotional needs of users instead of focusing only on basic functionality. Among emotional needs, the crucial role of the aesthetic quality of products is gradually being recognized in product design and marketing [25], [26]. Research has shown that the benefits that products provide to users include both hedonic and pragmatic aspects. Aesthetics is an important aspect of the hedonic benefits of products, and products with aesthetic appeal tend to have higher user ratings than standard products [27]. If a product's utilitarian value is greater than expected, this will lead to user satisfaction with the product and brand but will not guarantee brand loyalty. If a product's hedonic utility is greater than expected, consumers will be more loyal to a product or brand [27]. To increase users' brand loyalty, aesthetic quality as a hedonic benefit of a product is important.

Previous studies have noted that high and low visual aesthetics are the most dominant and typical dimensions for describing the aesthetic quality of products [28]. However, in actual product design research, higher dimensions are usually used to describe aesthetic quality, e.g. there are also medium visual aesthetics, medium-high visual aesthetics and medium-low visual aesthetics [8], [12].

### 2.2 Subjective and objective evaluation of the aesthetic quality of products

Currently, in studies of subjective evaluation, researchers usually conduct questionnaire research on users' aesthetic preferences by designing semantic scales and Likert scales as well as compensatory quantitative evaluation of the findings through various mathematical algorithms [29], [30], [31]. For example, Lógó et al. used semantic scales to collect aesthetic judgments and brand preferences that influence industrial design engineers and students in everyday product use. These authors also established a method for evaluating the aesthetics of everyday products based on an improved factor analysis approach [32]. Yadav et al. used Likert scales to collect subjective data on 12 aesthetic attributes of customers' perceptions of the appearance of cars. They combined the Kano model and fuzzy mathematical algorithm to compensate for the subjective data and calculate the relative importance of different aesthetic attributes [33].

In objective evaluation studies, researchers usually obtain objective data by measuring the pixel points or area of a product image and use mathematical algorithms to calculate the potential relationship between objective data and the product's beauty indicators to make an objective evaluation. Commonly used metrics include complexity, simplicity, balance, symmetry, contrast, purity and harmony. For example, Hsiao et al. obtained morphological parameters, such as the area ratio of the color of product components, by measuring the number of pixel dots in the component parts of a mobile phone product model. These authors combined image segmentation theory and planning mathematical algorithms to

calculate the correlation between morphological parameters and aesthetic indicators such as harmony and proposed a formula for measuring product aesthetics [34], [35]. Zhou et al. measured morphological parameters such as the position and area ratio of constituent parts in an image of an automotive product. These were combined with the nonlinear principal component analysis (NLPCA) method and nonlinear artificial fish swarm algorithm (NAFSA) to calculate the functional relationship between product morphological features and beauty indices such as symmetry, and proposed a design method based on quantitative aesthetic evaluation [36]. Since Birkhoff, the founder of computational aesthetics, proposed a mathematical model in 1993 for quantifying the degree of aesthetics as a ratio of order to complexity, prospective theoretical models, such as the tree of emotions, Plutchik's wheel of emotions and the circumplex model of affect, have been used for evaluation and decision-making in affective design and user experience design [13], [37].

In summary, research on the aesthetic quality evaluation of subjective and objective evaluations is relatively mature. Aesthetic preferences in subjective evaluation are influenced by factors such as personal taste and educational background, and aesthetic indicators such as order and harmony in objective evaluation are not very comprehensive. Nevertheless, previous studies have laid a solid foundation for research on the aesthetic quality evaluation of products and have had a wide impact [10], [38], [39].

### 2.3 Aesthetic quality evaluation based on fNIRS data

Physiological acquisition technologies (e.g., eye tracking and brain imaging) enable objective recording of data for the evaluation process. These technologies contribute to physiological data-based research on aesthetic quality evaluation, which has become an important research direction in product design and user experience [40]. In particular, fNIRS technology provides a new and convenient means for evaluating product aesthetic quality. fNIRS technology involves noninvasive and sustainable monitoring, can detect brain HBO<sub>2</sub> and HBR data in real time, and is able to capture the subtle brain activities of subjects. It is therefore widely used in the study of higher brain functions in aesthetic quality evaluation [15].

In studies applying the fNIRS technique for aesthetics evaluation, researchers have sought correlations between changes in fNIRS data (e.g., HBO<sub>2</sub> and HBR data) under different stimuli (e.g., paintings, faces, advertisements) or different aesthetic qualities (e.g., high visual aesthetics, medium visual aesthetics, and low visual aesthetics), with some important results [41]. Kawabat et al. used the fNIRS technique to explore brain changes during the evaluation of beautiful, neutral and unattractive paintings. These authors found that the perception of paintings of different aesthetic qualities is associated with different areas of the brain. For example, the left dorsolateral prefrontal area is stimulated when beautiful paintings are appreciated, while areas such as the active area of the anterior middle cortex and bilateral frontal areas are activated when unattractive paintings are

appreciated [42]. Balconi et al. used the fNIRS technique to explore brain changes during the aesthetic appraisal of attractive and unattractive faces and found significantly higher HBO<sub>2</sub> data in the right brain than in the left brain and lower HBR data for unattractive faces [43]. Kurahashi et al. used the NIRS technique to examine brain changes during the aesthetic evaluation of better-rated and poorly rated advertisements and found that better-rated advertisements caused an increase in HBO<sub>2</sub> data, demonstrating that NIRS can be applied to the advertising design of aesthetic quality ratings [44].

In addition, some research results of functional magnetic resonance imaging (fMRI) provide important ideas for this study. Different stimulus materials may also activate the right prefrontal cortex (painting) [28], orbitofrontal cortex and parietal lobes (painting) [45], orbitofrontal cortex and temporal areas (faces) [7], and temporal and parietal lobes (music) [46]. Aesthetic experience is likely to arise from interactions between the affective-evaluative, sensory-motor and meaning-knowledge nervous systems [7], [46]. The use of multimodal physiological data is becoming the most advanced technique in the field of affective computing. For example, a combination of multiple physiological data, such as fNIRS, fMRI, electroencephalogram (EEG), electromyogram (EMG), galvanic skin response (GSR) and blood pressure (BP), can be used for deeper exploration of user perception [19].

## III. USER EXPERIMENTS AND METHODS

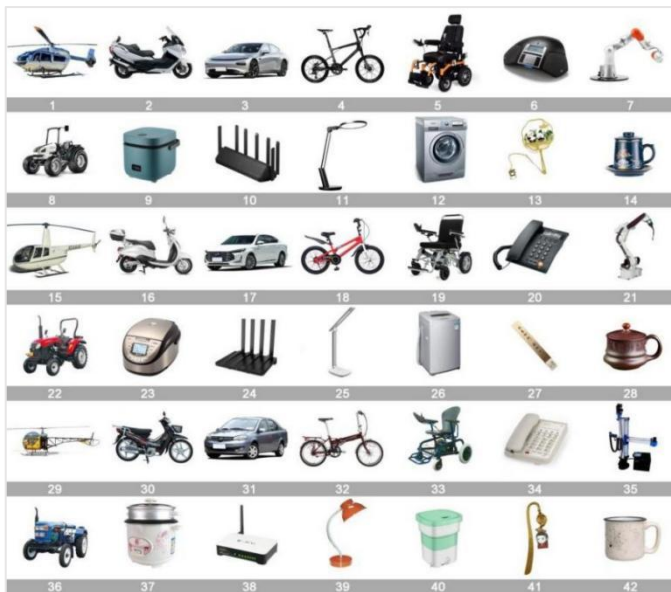
### 3.1 Stimulus materials

To simulate the process of assessing the aesthetic quality of a product, we chose 42 product images as the stimulus material for the fNIRS experiment. The 42 product images and numbers are shown in Figure 1. Our team of experts selected images of 4 major categories of products, transport, industrial equipment, lifestyle and cultural products, as stimulus materials based on the categories of entries for the Design Intelligent Awards of China (DIA) 2021. Within the 4 major categories, there were 14 subcategories. Among them, the transport category contained 4 subcategories, including aircraft, cars, motorbikes and bicycles; the industrial equipment category contained 4 subcategories, including wheelchairs, telephones, robots and tractors; the household products category contained 4 subcategories, including rice cookers, routers, table lamps and washing machines; and the cultural products category contained 2 subcategories, including cultural bookmarks (hereafter referred to as bookmarks) and cultural mugs (hereafter referred to as mugs). Cultural products are products designed by extracting elements of traditional Chinese culture, with mugs and bookmarks being the most widely designed [47]. The product images used for the experimental material were sourced from web searches. The product images were cleaned, labeled and standardized. Each product image was standardized to a white background and 2480\*2480 pixel size.

Defining the aesthetic quality of the product is to obtain the results of the public's subjective evaluation of the aesthetic quality of the experimental material, which provides basic data



support for subsequent data analysis and model construction. The aesthetic quality of the products was assessed based on the subjective total rating of the public. The results of the total rating reflect the overall level and concentrated trends in the public's evaluation of the aesthetic quality of stimulus materials, allowing for low attrition and rapid and accurate differentiation between categories [56]. We used the QuestionStar web-based questionnaire platform (<https://www.wjx.cn/>) to collect subjective ratings of the aesthetic quality of these products from 114 users (age 18-50, 64.04% male and 35.96% female) from different industries. The questionnaire asked the subjects to choose the score they thought was appropriate for the 70 product images according to their aesthetic preferences on a range of 1-7, with 1 being the lowest visual aesthetic quality and 7 being the highest visual aesthetic quality. After the questionnaire was completed, the data were exported by logging into the Questionnaire Star network questionnaire platform. Abnormal data of 4 users were eliminated, and the valid subjective scores of 110 users were added to arrive at the total subjective score. Finally, the aesthetic quality of the products was rated according to the total rating. The five product images in each subcategory were rated according to the total rating in descending order, with the highest 20% rated as high visual aesthetics, the middle highest 20% rated as middle high visual aesthetics, the middle 20% rated as middle visual aesthetics, the middle lowest 20% rated as middle lower visual aesthetics and the lowest 20% rated as low visual aesthetics.



**Fig. 1.** Forty-two images of products in the stimulus material with their numbers.

Finally, we selected 42 product images in three aesthetic quality classes (high visual aesthetic quality, medium visual aesthetic quality, and low visual aesthetic quality) as stimulus materials for the fNIRS experiment, and removed two scales (middle high visual aesthetic quality and middle low visual aesthetic quality). The use of predefined data on the aesthetic quality rating results of the stimulus materials allows for the

preemptive removal of stimulus materials with small differences in ratings, such as middle-high visual aesthetics and middle-low visual aesthetics in the present study. In this way, the accuracy of the evaluation of the aesthetic quality of the product can be improved, and the burden and fatigue of participants during the experiment can be reduced. Similarly, Balconi et al. [43] and Chikaho Kurahashi et al. [26] used fNIRS data to evaluate the aesthetic quality of advertisements and faces by preevaluating and screening the stimuli.

### 3.2 Experimental Subjects

A total of 50 subjects participated in the fNIRS acquisition experiment. The 50 subjects were all postgraduate students in the university; 24 were male and 26 were female. They were aged 22 to 30 years old, with an average age of 24 years. All subjects had normal or corrected-to-normal vision and were in good physical condition. The subjects were recruited through both online postings and publicity. The recruited subjects were very willing to participate in our experiment both because they were interested in the study and because they were told that they would receive monetary and material rewards for their participation. All subjects were fully informed and voluntarily signed written informed consent according to the Declaration of Helsinki. The study was approved by the Ethics Committee of the Faculty of Medicine of this university (approval number: ECSBMSSDU2022-1-53).

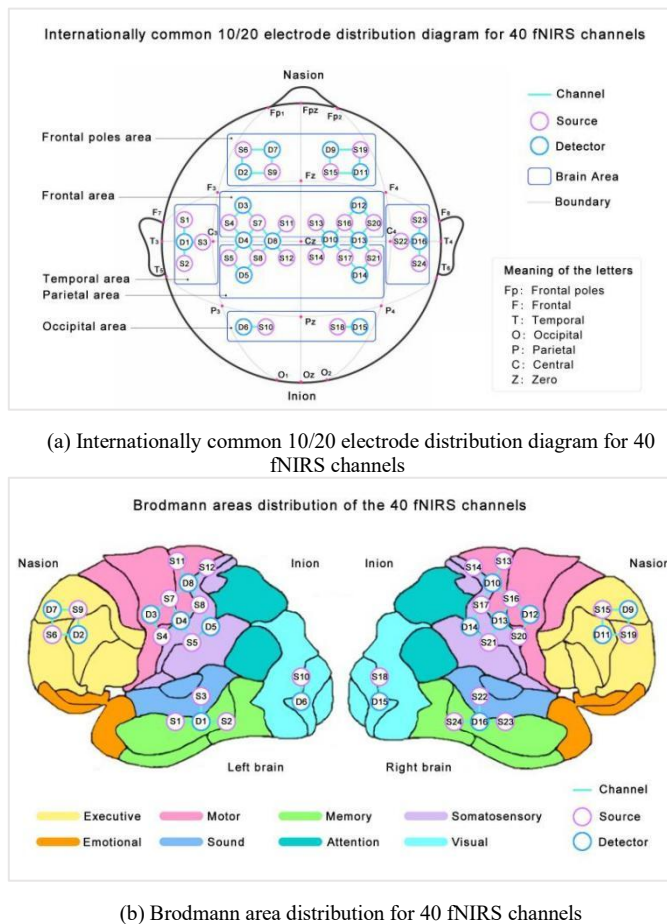
### 3.3 Experimental equipment

The fNIRS experiment was conducted using an fNIRS device manufactured by Danyang Huichuang Medical Equipment Co., Ltd., for data acquisition, equipped with Nirxmart software for fNIRS data recording. The fNIRS device has 40 signal detectors (SDs), 24 signal sources and 16 detectors at infrared wavelengths of 760 and 850 nm, respectively, and a sampling frequency of 10 Hz. Brain activity leads to an increase in oxygen consumption and is accompanied by an increase in cerebral blood flow due to neurovascular coupling, which results in changes in local  $\text{HbO}_2$ . Changes in  $\text{HbO}_2$  can be detected by fNIRS devices [41]. Functional NIRS is noninvasive and continuously monitorable and can capture subtle cortical activity in subjects [15]. In addition, fNIRS is a useful neuroimaging technique because it has lower cost and better portability than fMRI or PET [15].

### 3.4 Experimental procedure

The fNIRS experimental procedure uses a sequence effects psychology experimental paradigm to conduct experiments to reduce subjects' mental fatigue and improve the accuracy of the results [48], [49]. First, images such as experimental rules and stimulus materials were entered into Nirxmart software. Then, 28 SD probes in the fNIRS device were fixed in specific locations in a flexible helmet (prefrontal area, frontal area, parietal area, temporal area and occipital area) according to the international common 10/20 electrode allocation requirement and previous research results, and the distance between SD probes was set to 30 mm, forming 40 acquisition channels [43]. The fNIRS acquisition channel distribution is

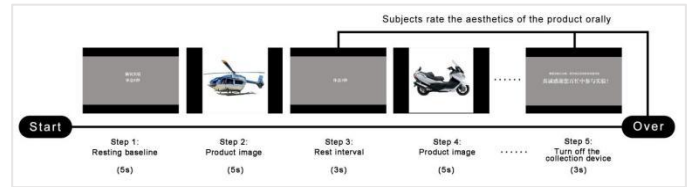
shown in Figure 2. After the 50 subjects entered the laboratory in sequence, they were invited to sit in a chair, adjusted to a comfortable sitting position and asked to wear the fNIRS helmet. Finally, the fNIRS device was connected to Nirxmart software to start the formal experiment. A 5-second resting baseline was recorded at the beginning of the experiment before the formal experiment began. For the formal experiment, 42 product images were presented to the subject in a chaotic order, with each product image presented for 5 s separated by a 3 s interval to respond to the participant's baseline, for a total duration of 336 s [43], [44]. During breaks, the subject was asked to dictate their ratings of the product images and was asked to rate the aesthetic quality of the stimulus material according to their aesthetic preferences (on a scale of 1-5, with 1 indicating low visual aesthetics and 5 indicating high visual aesthetics). The final ratings were manually recorded and summarized by a recorder [8]. The specific fNIRS experimental flow is shown in Figure 3.



**Fig. 2.** Distribution of fNIRS acquisition channels.

After the experiments, we used a bandpass filter (0.2-0.01 Hz) to denoise the fNIRS data and remove the interfering signals. We selected the HBO<sub>2</sub> data from the fNIRS data as the basis for data analysis and model construction using the first 45 datasets for data analysis and the last 5 datasets for validation of the results. The feasibility of continuous and noninvasive monitoring of HBO<sub>2</sub> data in the brain was first demonstrated by the initiator of NIRS (Jobsis) in 1977 [16].

According to previous studies, an increase in HBO<sub>2</sub> values or a decrease in HBR values is indicative of brain activity. However, HBO<sub>2</sub> data have a greater magnitude of signal change than HBR data, and HBO<sub>2</sub> data are more indicative of brain activity [50]. In addition, HBO<sub>2</sub> data have a better signal-to-noise ratio than HBR data [51].



**Fig. 3.** Experimental flow chart of fNIRS.

### 3.5 Data analysis and modeling methods

The correlation analysis function is used to analyze whether there is a correlation between the dependent and independent variables. For this purpose, the data were analyzed using the correlation analysis function in IBM SPSS Statistics 26 software. Prior to the correlation analysis, we used the regression analysis function in IBM SPSS Statistics 26 software to remove abnormal data from the dataset. In correlation analysis, the presence or absence of a relationship is usually determined using the statistical significance (Sig.) of the fNIRS data and the aesthetic quality of the product. The strength of the relationship is determined using the Pearson correlation of the fNIRS data and the aesthetic quality of the product. For example, Yan Shengchao et al. analyzed the correlation between network and time to achieve an accurate, real-time preview of network warnings [52]. Normally, a Pearson correlation with a significance of less than 0.05 (i.e.,  $p < 0.05$ ) indicates the existence of a correlation, and a larger correlation coefficient indicates a higher degree of correlation [53]. In this study,  $p < 0.05$  represented the correlation of a specific channel in a brain region. The HBO<sub>2</sub> data of this channel can be used for product aesthetic quality evaluation.

We used the multivariate logistic (M) analysis function in IBM SPSS Statistics 26 software to conduct an association analysis of the data to explore the logical relationship between the fNIRS data and product aesthetic quality. Logistic (M) is a classification method that is easy to use, fast, and shows the weights of individual features directly, among other features. It can easily absorb new data and build new models [55]. This is friendly to engineers and designers in actual design practice because an objective result can be obtained quickly without complex mathematical calculations. Generally, a significance of less than 0.05 is used to determine the existence of a relationship, and the regression coefficient B-value is used to determine what kind of relationship exists. The regression coefficient B-value indicates the average change in the dependent variable for each unit increase in the independent variable. The formula for calculating the B-value is the covariance of the independent variable and the dependent variable divided by the variance of the independent variable. The B-value is mainly dependent on the extent to which a

change in the independent variable affects the dependent variable. If the B-value is positive (or negative), it indicates a positive (or negative) relationship between the independent variable and the dependent variable. The larger (or smaller) the value of the regression coefficient B is, the larger and stronger (or smaller and weaker) the influence of the independent variable on the dependent variable. In this study, the calculation of the B-value was generated automatically with the help of SPSS Statistics 26 analysis software. Wald's test (Wald) is used to assess the B-value to determine whether the B-value is equal to 0. If the B-value is not equal to 0, the data are significant and can be used to construct an evaluation model based on the multivariate logistic (M) formula [54].

We constructed the product aesthetic quality evaluation model based on the multivariate logistic (M) model formula and the results of the multivariate logistic (M) analysis. The formulas of the multivariate logistic (M) model are shown in Equation (1), Equation (2) and Equation (3). Equation (1) is the expression of the dependent and independent variables, Equation (2) is the expression of the occurrence ratio of the dependent variable, and Equation (3) is the formula for the prediction and categorization of dependent variables [54]. The product aesthetic quality evaluation model is represented by Equation (4) to Equation (9). The model was constructed in two steps. In the first step, the constants of the product aesthetic quality evaluation model were defined as follows:  $G_1$ , high visual aesthetic quality;  $G_2$ , low visual aesthetic quality;  $G_3$ , medium visual aesthetic quality;  $Y_1$ , fNIRS data for the prefrontal area (S19-D11) channels;  $Y_2$ , fNIRS data for the frontal area (S4-D3) channels;  $Y_3$ , fNIRS data for the temporal area (S3-D1) channels; and  $Y_4$ , fNIRS data for the parietal area (S8-D8) channels. In the second step, the B value of the intercept in Table 4 was selected as the regression coefficient of the intercept, and the B value of each channel was selected as the regression coefficient of the fNIRS data of that channel. These sets of regression coefficients were used with the test data to construct Equations (4) and (5) according to the principle of linear summation. The values of  $G_1$  and  $G_2$  were calculated by constructing Equation (4) and Equation (5), while  $G_3$  was taken as the control group with a value of 0. The probabilities of occurrence of  $G_1$ ,  $G_2$  and  $G_3$  were determined according to the multivariate logistic (M) regression model as Equation (7), Equation (8) and Equation (9), respectively, where  $P(G_i)$  was the probability of occurrence of  $G_i$  and  $e$  was a constant (Euler's number) [53], [54]. Based on the above model, the values of  $G_1$ ,  $G_2$  and  $G_3$  can be calculated according to Equation (4), Equation (5) and Equation (6), respectively. The values of  $G_1$ ,  $G_2$  and  $G_3$  can be substituted into Equation (7) to obtain the probability of the product being of high visual aesthetic quality, into Equation (8) to obtain the probability of the product being of medium visual aesthetic quality, and into Equation (9) to obtain the probability of the product being of low visual aesthetic quality. A higher probability value is chosen to define the aesthetic quality of the product.

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n \quad (1)$$

$$e^Y = e^{\alpha + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n} \quad (2)$$

$$P_{(Y)} = \frac{e^Y}{1 + e^Y} = \frac{e^{\alpha + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n}}{1 + e^{\alpha + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n}} \quad (3)$$

$Y$  is the dependent variable,  $\alpha$  is the intercept value,  $\beta_1$  to  $\beta_n$  are the regression coefficients of the independent variables  $X_1$  to  $X_n$ ,  $X_1$  to  $X_n$  are the independent variables from 1 to  $n$ ,  $e$  is a natural constant,  $e^Y$  is the incidence of the dependent variable  $Y$ , and  $P_{(Y)}$  is the prediction accuracy of the dependent variable  $Y$ .

$$G_1 = 2.846 + 263.483 * Y_1 + 30.632 * Y_2 + 29.493 * Y_3 + 15.882 * Y_4 \quad (4)$$

$$G_2 = -1.702 - 204.078 * Y_1 - 17.532 * Y_2 \quad (5)$$

$$G_3 = 0 \quad (G_3 \text{ is the control group}) \quad (6)$$

$$P_{(G_1)} = \frac{e^{G_1}}{e^{G_1} + e^{G_2} + e^{G_3}} \quad (7)$$

$$P_{(G_2)} = \frac{e^{G_2}}{e^{G_1} + e^{G_2} + e^{G_3}} \quad (8)$$

$$P_{(G_3)} = \frac{e^{G_3}}{e^{G_1} + e^{G_2} + e^{G_3}} \quad (9)$$

We verified the consistency of the aesthetic quality of the predefined stimulus material with the subjective perceived aesthetic quality of the subjects. The correlation and association analysis between fNIRS data and product aesthetic quality used the product aesthetic quality as defined by the results of the prepopular evaluation of the aesthetic quality of the stimulus material. That is, the definition of product aesthetic quality was generated on an average basis rather than from a correlation and association analysis of the subjects' fNIRS data and subjective ratings. Subjective evaluation data were obtained by recording the evaluation scores of the subjects on the aesthetic rating of the product during the experiment. The 50 participants were asked to record the ratings by hand according to their aesthetic preferences (the users' subjective scoring range was 1-5, with 1 being the lowest visual aesthetics and 5 being the highest visual aesthetics). Finally, we conducted a statistical summary based on the recorded data and the table of the subjects' total subjective ratings and product aesthetic quality ratings. Moreover, To verify the validity of the product aesthetic quality evaluation model, the accuracy of the product aesthetic quality prediction was verified, and the last five sets of never-before-used fNIRS data were used.

## IV. RESULTS

### 4.1 Results of defining the aesthetic quality of a product

The total subjective product aesthetic quality score and aesthetic quality rating scale are shown in Table 1.

TABLE I  
TOTAL SUBJECTIVE PRODUCT AESTHETIC QUALITY SCORE  
AND AESTHETIC QUALITY RATING SCALE FOR 14  
SUBCATEGORIES.

Aesthetic quality Grade (Score value ranges)	Product category and overall subjective rating													
	Aircraft	Car	Motorbike	Bicycle	Robot	Wheelchair	Telephone	Tractor	Washing machine	Router	Rice Cooker	Table lamp	Bookmark	Mug
High visual aesthetics (479-607)	524	582	607	527	535	479	591	592	603	549	524	492	539	540
Middle high visual aesthetics (397-562)	510	562	463	492	507	397	502	508	501	494	442	418	509	523
Medium visual aesthetics (380-497)	497	492	446	451	460	380	492	441	412	480	432	391	477	490
Middle low visual aesthetics (325-485)	463	476	442	465	457	375	485	439	412	466	325	375	472	463
Low visual aesthetics (320-446)	441	367	358	420	374	336	435	366	323	344	320	366	446	406

The aesthetic quality scale of the 42 product images in the stimulus material is shown in Table 2, and the 42 product images in the stimulus material and the numbered diagram are shown in Figure 1.

TABLE II  
AESTHETIC QUALITY SCALE FOR THE 42 PRODUCT IMAGES IN THE STIMULUS MATERIAL.

Projects	Contents										
Image serial number	1	2	3	4	5	6	7	8	9	10	11
Product category	Aircraft	Motorbike	Car	Bicycle	Wheelchair	Telephone	Robot	Tractor	Rice Cooker	Router	Table lamp
Score value	524	607	582	527	479	591	535	592	524	549	492
Aesthetic quality level	High	High	High	High	High	High	High	High	High	High	High
Image serial number	12	13	14	15	16	17	18	19	20	21	22
Product category	Washing machine	Bookmark	Mug	Aircraft	Motorbike	Car	Bicycle	Wheelchair	Telephone	Robot	Tractor
Score value	603	539	540	497	446	492	451	380	492	460	441
Aesthetic quality level	High	High	High	Medium	Medium	Medium	Medium	Medium	Medium	Medium	Medium
Image serial number	23	24	25	26	27	28	29	30	31	32	33
Product category	Rice Cooker	Router	Table lamp	Washing machine	Bookmark	Mug	Aircraft	Motorbike	Car	Bicycle	Wheelchair
Score value	432	480	391	412	477	490	441	358	367	420	336
Aesthetic quality level	Medium	Medium	Medium	Medium	Medium	Medium	Low	Low	Low	Low	Low
Image serial number	34	35	36	37	38	39	40	41	42		
Product category	Telephone	Robot	Tractor	Rice Cooker	Router	Table lamp	Washing machine	Bookmark	Mug		
Score value	435	374	366	320	344	366	323	446	406		
Aesthetic quality level	Low	Low	Low	Low	Low	Low	Low	Low	Low		

#### 4.2 Correlation analysis of fNIRS data with product aesthetic quality

The results of the correlation analysis between the fNIRS data and the aesthetic quality of the product are shown in Table 3. According to the results of the analysis in Table 3, of the 40 channels of fNIRS data, eight channels with fNIRS data significance below 0.05 showed a significant correlation with product aesthetic quality: the temporal region (S3-D1), prefrontal region (S19-D11), frontal region (S4-D3, S7-D8 and S16-D10), parietal region (S8-D5 and S8-D8) and occipital regions (S18-D15). Equally importantly, Pearson correlations of the fNIRS data for the eight channels mentioned above showed that the strength of the relationships, in descending order (absolute value of correlation from largest to smallest), was as follows: prefrontal areas (S19-D11) > parietal areas (S8-D8) > frontal areas (S4-D3) > frontal areas (S7-D8) > temporal areas (S3-D1) > parietal areas (S8-D5) > frontal areas (S16 -D10) > occipital regions (S18-D15), with fNIRS data from prefrontal (S19-D11), parietal (S8-D8) and frontal (S4-D3) regions showing strong correlations with product aesthetic quality.

The analysis showed that data from the temporal, prefrontal, frontal, parietal and occipital areas were significantly associated with product aesthetic quality. The fNIRS data from 8 of the 40 channels had a high correlation and confidence level with product aesthetic quality; that is, fNIRS data from these 8 channels could be used to evaluate product aesthetic quality.



TABLE III  
RESULTS OF THE CORRELATION ANALYSIS BETWEEN fNIRS DATA AND PRODUCT AESTHETIC QUALITY FOR 40 CHANNELS.

Category	Contents									
No.	S1-D1	S2-D1	S3-D1	S4-D3	S4-D4	S5-D4	S5-D5	S6-D2	S6-D7	S7-D3
Pearson correlation	-0.041	-0.043	-0.240**	-0.370**	-0.009	-0.086	-0.049	0.008	-0.046	-0.026
Sig.	0.502	0.48	0	0.001	0.88	0.16	0.427	0.891	0.455	0.671
No.	S7-D4	S7-D8	S8-D4	S8-D5	S8-D8	S9-D2	S9-D7	S10-D6	S11-D8	S12-D8
Pearson correlation	0.061	-0.290**	-0.003	-0.220**	-0.389**	0.018	0.017	0.03	0.011	0.036
Sig.	0.318	0.001	0.964	0	0	0.764	0.787	0.628	0.852	0.558
No.	S13-D10	S14-D10	S15-D9	S15-D11	S16-D10	S16-D12	S16-D13	S17-D10	S17-D13	S17-D14
Pearson correlation	-0.094	-0.004	-0.036	0.024	-0.217**	-0.02	0.049	0.08	0.005	0.042
Sig.	0.126	0.942	0.558	0.69	0	0.746	0.423	0.19	0.932	0.495
No.	S18-D15	S19-D9	S19-D11	S20-D12	S20-D13	S21-D13	S21-D14	S22-D16	S23-D16	S24-D16
Pearson correlation	-0.182**	0.026	-0.837**	0.009	-0.033	-0.006	-0.019	0.068	-0.014	0.05
Sig.	0.003	0.669	0	0.886	0.595	0.92	0.752	0.264	0.819	0.412



Fig. 4. Average statistics of the fNIRS data.

In the correlation analysis between fNIRS data and product aesthetic quality, we calculated the average values of fNIRS data for each of the eight channels mentioned above and attempted to distinguish and evaluate the product aesthetic quality through the average values.

The statistical plot of the fNIRS data average values for the temporal area (S3-D1) channels is shown in Figure 4. According to the statistical results in Figure 4, the fNIRS data average values for the temporal area (S3-D1) channels differed in the aesthetic quality of the products, but there was no clear distribution pattern. For example, in aircraft products, the lowest average values were found for high visual

aesthetics and the highest were found for low visual aesthetics. In robotic products, the highest average values were found for high visual aesthetics and the lowest were found for low visual aesthetics. Similarly, we found no clear distribution pattern in the product aesthetic quality for the average values of fNIRS data for the other channels.

The analysis demonstrated that it is difficult to directly differentiate and evaluate product aesthetic quality using the average values of the fNIRS data. Evaluating the aesthetic quality of a product solely through the average of fNIRS data is likely to result in a failure to evaluate the aesthetic quality of the product.

#### 4.3 Association analysis of fNIRS data with product aesthetic quality

The results of the association analysis between the fNIRS data and the aesthetic quality of the product are shown in Table 4. According to the results of the analysis in Table 4, among the data evaluated as having high visual aesthetic quality, the fNIRS data of the frontal (S4-D3), temporal (S3-D1), parietal (S8-D8) and prefrontal (S19-D11) areas, with significance values less than 0.05, had an influential relationship with high visual aesthetic quality in these four channels. The fNIRS data of these four channels were positively correlated with high visual aesthetic quality, while the fNIRS data of the other channels were not correlated with high visual aesthetic quality. Again, it can be seen that in the data with the evaluation code of low visual aesthetic quality, the significance values for the parietal area (S8-D8) and the prefrontal area (S19-D11) were below 0.05, and the fNIRS data for these 2 channels had an influential relationship with low visual aesthetic quality. The fNIRS data from these 2 channels were negatively correlated with low visual aesthetic quality, while the fNIRS data from the other channels were not correlated with mid-visual aesthetic quality. The fNIRS data for mid-visual aesthetic quality appeared as a control group in the multivariate logistic (M) analysis and therefore does not appear in the results of the analysis in Table 4.

After the association analysis of the fNIRS data with the aesthetic qualities of the product, we examined the activation

maps of the subjects' brain areas according to different aesthetic qualities. The activation map of the subjects' brain areas according to different aesthetic qualities is shown in Figure 5. Figure 5 was automatically generated by NirSpark software based on the values of  $\text{HbO}_2$  in the fNIRS data. In Figure 5, red represents positive activation of brain regions, while blue represents negative activation of brain regions. As shown in Figure 5, more brain areas are activated for high and medium visual aesthetic qualities than for low visual aesthetic qualities. Moreover, most of the brain areas with high and medium visual aesthetic qualities showed positive activation, whereas most of the brain areas with low visual aesthetic qualities showed negative activation. This suggests that different product aesthetic qualities activate different brain areas.

The analysis shows that there is a logical relationship between fNIRS data and product aesthetic quality. Among the eight channels with significant correlations, fNIRS data from four channels had an influence on high visual aesthetic quality, and all of them showed positive correlations. fNIRS data from two channels had an influence on low visual aesthetic quality, and all of them showed negative correlations. Based on the analysis results in Table 4 and the multivariate logistic (M) model formula, a product aesthetic quality evaluation model can be constructed to differentiate product aesthetic quality.

TABLE IV  
RESULTS OF MULTIVARIATE LOGISTIC (M) ANALYSIS.

Evaluation code	Category	B	Wald	Significance
High Vision Aesthetics	Intercept distance	-2.846	31.43	0
	S3-D1	29.493	9.001	0.003
	S4-D3	30.632	7.628	0.006
	S7-D8	10.888	1.993	0.158
	S8-D5	4.272	0.266	0.606
	S8-D8	15.882	5.477	0.019
	S16-D10	5.593	0.729	0.393
	S18-D15	0.783	0.011	0.917
	S19-D11	263.483	39.703	0
	Intercept distance	-1.702	27.686	0
Low Vision Aesthetics	S3-D1	-12.081	2.555	0.11
	S4-D3	4.948	0.277	0.599
	S7-D8	-6.343	0.922	0.337
	S8-D5	-10.507	1.94	0.164
	S8-D8	-17.532	8.242	0.004
	S16-D10	-1.624	0.078	0.78
	S18-D15	2.425	0.137	0.712
	S19-D11	-204.078	39.96	0
	Intercept distance	-1.702	27.686	0
	S3-D1	-12.081	2.555	0.11

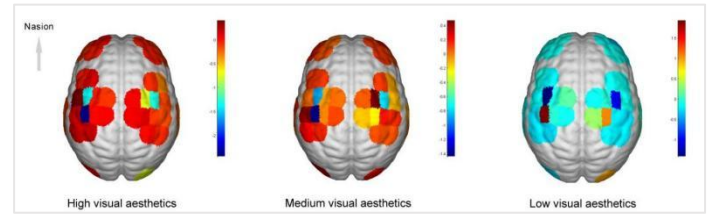


Fig.5. Activation of brain areas in a subject with different aesthetic qualities.

#### 4.4 Construction of a product aesthetic quality evaluation model

The overall prediction accuracy of the product aesthetic quality was 84.1% according to the classification table of the analytical results of the multivariate logistic (M), which is shown in Table 5. The model's prediction accuracy was 90.0% for high visual aesthetic quality, 85.5% for low visual aesthetic quality, and 76.7% for medium visual aesthetic quality.

These results indicates that the product aesthetic quality evaluation model we constructed has high accuracy in evaluating the product aesthetic quality, and the product aesthetic quality can be predicted from the channel-specific fNIRS data.

TABLE V

CLASSIFICATION RESULTS OF MULTIVARIATE LOGISTIC (M) ANALYSIS.

Actual test	Predictions			
	Low	High	Medium	Percentage correct
High visual aesthetics	1	81	8	90.0%
Low visual aesthetics	77	0	13	85.5%
Medium visual aesthetics	10	12	68	76.7%
Overall percentage	32.6%	34.4%	33.0%	84.1%

#### 4.5 Results of aesthetic quality consistency validation of experimental materials

The table of the subjects' total subjective ratings and product aesthetic quality ratings is shown in Table 6. We ranked each subcategory in order from the highest to the lowest rating, with the highest rating designated as high visual aesthetic quality, the medium rating designated as medium visual aesthetic quality, and the lowest rating designated as low visual aesthetic quality. Table 6 shows that the images numbered 1-14 are all defined as having high visual aesthetic quality, while the images numbered 29-42 are all defined as having low visual aesthetic quality. This is consistent with the aesthetic quality rating of the product images in the stimulus material in Table 2. The predefined aesthetic quality ratings of the experimental materials have validity, and it is feasible to use the predefined aesthetic quality ratings of the experimental materials to construct an evaluation model for the aesthetic quality of the products.

TABLE VI  
SUBJECTIVE TOTAL RATINGS OF SUBJECTS AND PRODUCT AESTHETIC QUALITY RATINGS.

Projects	Contents										
Image serial number	1	2	3	4	5	6	7	8	9	10	11
Subjects' total score	206	233	243	218	231	199	236	234	240	215	210
Aesthetic quality level	High	High	High	High	High	High	High	High	High	High	High
Image serial number	12	13	14	15	16	17	18	19	20	21	22
Subjects' total score	188	212	221	165	173	166	146	171	123	154	131
Aesthetic quality level	High	High	High	Medium	Medium	Medium	Medium	Medium	Medium	Medium	Medium
Image serial number	23	24	25	26	27	28	29	30	31	32	33
Subjects' total score	104	187	148	104	136	147	116	77	48	93	86
Aesthetic quality level	Medium	Medium	Medium	Medium	Medium	Medium	Low	Low	Low	Low	Low
Image serial number	34	35	36	37	38	39	40	41	42		
Subjects' total score	37	106	49	30	46	36	85	86	64		
Aesthetic quality level	Low	Low	Low	Low	Low	Low	Low	Low	Low		

#### 4.6 Evaluation of model accuracy validation results

The results of the accuracy validation of the product aesthetic quality prediction are shown in Table 7. The product aesthetic quality evaluation model has the highest accuracy in predicting high visual aesthetics at 100.0%, low visual aesthetics at 90.0% and medium visual aesthetics at 80.0%, with an average correct rate of 90.0%. This demonstrates good overall performance, which is also broadly consistent with the recognition accuracy in the previous results classification table.

The validation results show that the product aesthetic quality evaluation model performs better overall in terms of prediction accuracy, especially for highly visually aesthetic products. The product aesthetic quality evaluation model is valid and can be used for the quantification and evaluation of product aesthetic quality.

Table VII

RESULTS VALIDATING THE ACCURACY OF PRODUCT AESTHETIC QUALITY PREDICTIONS.

Actual test	Predictions			Percentage correct
	Low	High	Medium	
High visual aesthetics	0	10	0	100.00%
Low visual aesthetics	9	0	1	90.00%
Medium visual aesthetics	2	0	8	80.00%
Overall percentage	33.30%	33.30%	33.30%	90.00%

## V. DISCUSSION

In the field of product design research, product aesthetic quality is an important factor that influences users' purchase intention and consumption behavior [40]. In this study, we answer the question of whether fNIRS data can be used to evaluate product aesthetic quality by analyzing the correlation between fNIRS data and product aesthetic quality. We construct a product aesthetic quality evaluation model with higher accuracy based on the multivariate logistic (M) algorithm, which provides engineers and designers with an objective and accurate decision-making reference. This is our main contribution and innovation to the existing theory of

product aesthetics evaluation, the application of fNIRS data and the application of the multivariate logistic (M) algorithm.

Our results show that fNIRS data from eight of the 40 channels collected by the fNIRS technique have high correlation and reliability for evaluating product aesthetic quality: temporal regions (S3-D1), prefrontal regions (S19-D11), frontal regions (S4-D3, S7-D8 and S16-D10), parietal areas (S8-D5 and S8-D8) and occipital areas (S18-D15). This finding is in general agreement with the results of other researchers using fNIRS, fMRI and MEG, where product aesthetic quality evaluations involved prefrontal and frontal areas related to higher cognition [28], [42], [57], parietal areas related to movement [46], temporal areas related to reward [1], and occipital areas related to vision [7].

It is difficult to differentiate and evaluate product aesthetic quality directly using the average values of the fNIRS data. Evaluating product aesthetic quality through the average values of fNIRS data alone is likely to result in a failure of product aesthetics evaluation. This is not entirely consistent with the findings of Balconi et al. [43] and Kurahashi et al. [44], who used fNIRS and NIRS techniques. Although there are differences in HBO<sub>2</sub> data in product aesthetic quality, there is no clear pattern of distribution, which may be due to different stimulus materials inducing different oxygen and hemoglobin data changes [7], [20], [58].

We also found a logical relationship between fNIRS data and product aesthetic quality in the multivariate logistic (M) analysis. Among the eight channels with significant correlations, four channels of fNIRS data had an influential relationship with high visual aesthetic quality. All of them showed positive correlations, and four were prefrontal (S19-D11), frontal (S4-D3), temporal (S3-D1) and parietal (S8-D8) regions. Two channels of fNIRS data were associated with low visual aesthetic quality. The fNIRS data showed complex correlations in two channels, the prefrontal (S19-D11) and parietal (S8-D8) areas. Regarding the strength of the relationship, the prefrontal area (S19-D11) was the most influential, which is highly consistent with the results of other researchers [28], [42], [57]. With regard to the number of channels activated by different visual aesthetic qualities, the

results of the present study are consistent with those of Michela Balconi et al., suggesting that different visual aesthetic qualities induce changes in oxyhaemoglobin data in different brain regions [43]. By examining the association of fNIRS data in the classification of product aesthetic quality through multivariate logistic (M) analysis, an evaluation model to differentiate product aesthetic quality can be constructed.

Equally importantly, we constructed a product aesthetic quality evaluation model that predicts high visual aesthetic quality, medium visual aesthetic quality and low visual aesthetic quality based on the results of the association analysis and the multivariate logistic (M) model formulation. The model can obtain the results of product aesthetic quality evaluation based on subjects' fNIRS data. It has high accuracy in the evaluation of product aesthetic quality, with an overall evaluation accuracy of 84.1%. The model has the highest accuracy of 90.0% for the evaluation of highly visually aesthetic quality and the lowest accuracy of 76.7% for the evaluation of medium visually aesthetic products. This shows that the quality evaluation model for product aesthetics can distinguish product aesthetic quality well. This is in accordance with the results of Louisa Kulke et al.'s research on emotion recognition, which used facial surface EMG signals to evaluate happy and angry expressions and found that neutral expressions were not recognized better [59].

We verified the consistency of the aesthetic quality of the stimulus material with the subjective aesthetic quality ratings of the subjects and the validity of the product aesthetic quality evaluation model. The aesthetic qualities of the stimuli may not be consistent with the subjective aesthetic quality ratings of the subjects. If the inconsistency is due to deceptive subjective data or the subject's own specificity, the accuracy of the model will be reduced, and there is a risk of failure of the evaluation. The validation results show that the aesthetic quality of the stimulus materials in this study was consistent with the subjective aesthetic quality ratings of the subjects and that the product aesthetic quality evaluation model was valid. Furthermore, the overall accuracy of the predictions of the product aesthetic quality evaluation model was good and could be used for the quantification and evaluation of product aesthetic quality.

Although the results are encouraging, we should highlight two shortcomings in our study. First, a number of factors influence fNIRS data; however, it is unknown how these factors affect the evaluation of the aesthetic quality of a product. Examples include people (factors such as design experience and literacy) [37], [38], features (factors such as complexity of form and color harmony) [39] and experimentation (factors such as fatigue and cognitive load) [60]. These factors are by no means a complete enumeration of the aesthetic qualities of a product. Therefore, our findings do not explore which factors influence product aesthetic quality; instead, we examine whether fNIRS technology can be used to assist humans in evaluating the aesthetic qualities of product design. Birkhoff, the founder of computational aesthetics, proposed a relationship from order to complexity

and aesthetic rating, but it is extremely difficult to identify a relationship between these factors and product aesthetic rating [9], [61]. Second, we used the well-established multivariate logistic (M) algorithm in SPSS software to explore the association between fNIRS data and product aesthetic quality. However, the logical relationship between the obtained fNIRS physiological indicators and the aesthetic quality of the product was not strong, so more powerful mathematical algorithms are worth considering. For example, generative adversarial neural networks (GANs), artificial neural networks (ANNs) and convolutional neural networks (CNNs) can enable deep mining of fNIRS data, which may lead to the construction of a highly relevant association and highly accurate product aesthetic quality evaluation model [62], [63].

In conclusion, our study shows that fNIRS data can be used for product aesthetic evaluation and that the evaluation model can distinguish product aesthetic quality well enough to provide engineers and designers with an objective and accurate decision-making reference to help them make informed choices in the product development process [24]. Although the shortcomings of this study may affect the accuracy of the evaluation model, the correlation analysis and the construction of the product aesthetic quality evaluation model can provide ideas for other research scholars. The potential contribution of using fNIRS data to evaluate product aesthetic quality is important and provides a solid basis for future aesthetic quality evaluations.

In actual design practice, designers and managers usually rely on experience and intuition without a scientific basis for the evaluation of product aesthetic quality. Although the use of fNIRS technology is more expensive and complex than subjective measurement, fNIRS technology provides a more credible scientific basis. With the help of the evaluation model, product aesthetic quality can be processed quickly and in bulk [24]. Especially for expensive and large-scale projects, inexperienced and novice designers can be guided by the product aesthetic quality evaluation model to complete an accurate evaluation.

Among the theoretical contributions, this study complements aesthetic evaluation theories in the field of user experience and affective computing, provides new ideas to avoid the decision errors and risks caused by design evaluation in the early stage, promotes the modernization of product aesthetic quality evaluation methods and advances the development of product design evaluation theory. The findings are also applicable to the fields of graphic design, clothing design and architectural design and could also serve as a benchmark for artificial intelligence to perform the function of aesthetic perception.

## VI. CONCLUSION

This study aimed to provide insights into the use of fNIRS data to assist humans in evaluating product aesthetic quality as a cue and reference to guide product design. The results show that it is possible to evaluate the aesthetic quality of products using fNIRS data and that our constructed model for evaluating the aesthetic quality of products can distinguish the



aesthetic quality of products well. The main findings of this study are as follows.

- The fNIRS data from 8 of the 40 channels collected by the fNIRS technique have a high correlation and confidence level with product aesthetic quality and can be used for evaluation. It is difficult to directly use the averaged values of the fNIRS data to differentiate and evaluate the aesthetic quality of products.
- In the association analysis, there is a logical relationship between the fNIRS data and the aesthetic quality of the product in four of the eight channels mentioned above. The association between fNIRS data in the classification of product aesthetic quality was explored through multivariate logistic (M) analysis.
- We constructed a product aesthetic quality evaluation model that predicts high visual aesthetic quality, medium visual aesthetic quality and low visual aesthetic quality based on the results of the association analysis and the multivariate logistic (M) model formula. The overall accuracy of this evaluation model reached 84.1%. Moreover, the product aesthetic quality evaluation model is particularly accurate in identifying product images with high visual aesthetics, with an accuracy rate of 90.0%.

In our future work, we will explore integrated multimodal physiological data as well as the factors that affect the variation in physiological data. In addition, we will introduce more powerful algorithms to construct a product aesthetic quality evaluation model to provide engineers and designers with more comprehensive and accurate references.

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**Yong Wang** (Member, IEEE) obtained his Master of Engineering degree in Vehicle Engineering from the Department of Mechanical Engineering, North China Electric Power University, Baoding, Hebei Province, China in 2017. He is currently studying for his doctorate at The School of Mechanical Engineering, Shandong University, Jinan, Shandong

Province, China. His research areas are aesthetic computing, design aesthetic, industrial design and color matching design.

He has received more than 60 awards and honors include a National Scholarship (Ministry of Education, PRC) and a Rising Star Award in the Shandong Provincial Governor Cup Industrial Design Competition.



**Fanghao Song** obtained his Doctor of Arts degree in aesthetic cultures from the Aesthetics of Literature and Art Research Center, Shandong University, Jinan, Shandong Province in 2017. Since 1998, he has been an associate professor and doctoral supervisor in the School of Mechanical Engineering, Shandong University, and the director of the Institute

of Modern Industrial Design.

His research areas are interaction design, design aesthetic, and industrial design. He became a senior member of the Industrial Design, Society of China Mechanical Engineering Society in 2014 and a member of the Interaction Design Committee of China Industrial Design Association in 2013.



**Yan Liu** obtained her Doctor of Arts degree in folk art from the School of Arts, Shandong University, Jinan, Shandong Province, China in 2016. Since 1998, she has been a professor and doctoral supervisor at the School of Mechanical Engineering, Shandong University, and the director of the Department of Industrial Design of the School of

Mechanical Engineering. Her research interests include design, color design, and design aesthetic. She became a senior member of the Industrial Design Society of China Mechanical Engineering Society in 2014 and a director of the Shandong Folk Artists Association in 2017.



**Yaying Li** (Member, IEEE) graduated from Taiyuan University of Technology in Taiyuan, Shanxi province, China in 2015 with a bachelor's degree in Art and Design. Since 2016, she has been studying for a PhD at the School of Mechanical Engineering, Shandong University, Jinan, Shandong Province, China. Her research fields are industrial design, Intelligent

vehicle interface design.



**Weihao Wang** obtained his Master of Engineering degree in the School of Mechanical Engineering at Shandong University. He is currently studying for his doctorate at The School of Mechanical Engineering, Shandong University, Jinan, Shandong Province, China. He majored in industrial design engineering, while his research interests are interaction design

and human-computer interaction.



**Qiqi Huang** obtained her master's degree in design from the School of Mechanical Engineering, Shandong University, China in 2023. She is currently pursuing a PhD degree in the School of Computer Science and Informatics at Cardiff University, Wales, UK. Her research area is human-computer interaction.



**Yang Hu** majored in product design at the School of Mechanical Engineering, Shandong University. She is currently pursuing a master's degree in design from Shandong University in Jinan, China. Her main research interests are interaction design, design color and design aesthetics. She has won many awards such as the third prize of iCAN International

Innovation and Entrepreneurship Competition and the first prize of Shandong College Students Industrial Design Competition.