Research on the Evaluation Model for the Tactile Feel of Custom Wardrobe Furniture Finishes

Yushu Chen and Zixin Xu *

The decision-making process of consumers regarding custom wardrobe furniture transcends product functionality to include the sensory experience, notably the tactile aspect. This study focuses on the tactile experience to assist consumers in evaluating the tactile feel of custom wardrobe finishes, such as cognitive fuzziness during the experience, the challenge of clearly describing the connection between touch sensation and the physical attributes of the custom wardrobe, and reducing communication costs between users and designers. The research first clarifies the hierarchical cognitive structure of the tactile sensation of custom wardrobe finishes, then explores the logical relationships between levels through linear regression models. Subsequently, a nonlinear relationship model between the “Physical Attributes Layer” and the “Tactile Sensation Layer” is constructed using a Backpropagation Neural Network, and the connection between the “Tactile Sensation Layer” and the “Comprehensive Evaluation Layer” is mapped through a multiple linear regression equation. This comprehensive evaluation system for the tactile feel of custom wardrobe finishes provides designers with a tool to optimize the tactile characteristics of products, thereby shortening the design iteration cycle and improving design precision. It also helps users better express their emotional needs in terms of tactile sensations, enhancing the connection between tactile experience and emotion.

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INTRODUCTION

The rise of customized furniture signifies a shift in the furniture industry from mass production to a focus on personalization and consumer involvement, aligning with the growing demand for individual expression and customized products. This shift reflects consumers’ pursuit of furniture that meets personal aesthetic and functional needs, driving an increase in preferences for more personalized and meaningful products (Pedrazzoli *et al*. 2014). Advances in production technology, especially the application of Computer-Aided Design (CAD) and 3D printing technologies, have removed barriers between traditional production and customization, making custom furniture appealing not just to the high-end market but to a broader audience (Murmura and Bravi 2017). The development of the digital marketplace offers consumers a platform for full participation from design to material selection, ensuring products better reflect personal preferences. Moreover, custom furniture design integrates multisensory experiences including touch, hearing, and smell, enriching user interaction and emphasizing the importance of sensory elements in fulfilling emotional needs and enhancing satisfaction (Sakamoto and Watanabe 2017). This sensory-centric design philosophy, which is closely tied to contemporary furniture needs, not only provides visual and emotional pleasure but also deepens physical interaction with users, marking a significant evolution towards more personalized and consumer satisfaction-oriented furniture design (Saxena *et al*. 2023).

As consumers increasingly seek personalization in both the form and substance of furniture, the tactile quality of wardrobe finishes emerges as a crucial element, significantly affecting user satisfaction and engagement. Touch, as a primary sensory channel, conveys delicate information about material temperature, texture, and quality. In custom wardrobes, every detail is tailored to personal preferences; for instance, a smooth, delicate wood finish might evoke warmth and a connection to the natural world, whereas a cool, sleek metal finish might appeal to those seeking minimalism and contemporary aesthetics, with its smoothness suggesting precision and modernity (Ornati 2019). Therefore, the choice of finish in custom wardrobes is not a trivial aspect of design but a thoughtful decision aligned with users' sensory expectations and lifestyles. The tactile response elicited by different materials can significantly affect the overall perception of the wardrobe, including feelings of comfort, luxury, or practicality, especially in personal spaces such as bedrooms, where the sensory quality of furniture contributes to the atmosphere and emotional tone. Additionally, emphasizing the tactile experience in custom wardrobe finishes reflects a growing awareness of the psychological impact of touch. Studies have shown that tactile perception can affect mood and stress levels, highlighting the importance of tactile design in creating an aesthetically pleasing and psychologically comfortable environment (Jang and Ha 2021). By integrating tactile considerations into the design and customization process, manufacturers and designers are expanding the narrative of what furniture can be—not just a visual interaction with objects but a dialogue between objects and human sensory organs (Tavakoli 2014).

Although the furniture industry has made progress in customization practices, sensory research on furniture finishes has been primarily focused on the visual aspect, with relatively little exploration of the tactile sense. How touch influences consumer preferences for customized furniture and interaction with it remains under-explored. Inspiration can be gleaned from other related fields of haptic research, which recently has focused on three primary levels: emotion and sentiment, tactile perception, and the physical properties of materials. At the level of emotion and sentiment, identifying a product's intangible characteristics—such as semantics, associations, emotions, and values—is crucial before selecting descriptive terms. For instance, "comfort" is a common descriptor in textiles and apparel research, whereas "surprise" and "pleasure" are used to convey emotions in gift packaging studies. In the realm of tactile perception, Tang *et al.* (2017) analyzed the principles of visual-tactile experience testing for thirty-eight types of automotive interiors. They developed an evaluation system and model to address the challenges posed by both personalized custom products and mass-produced items, continually amassing data on the material preferences and equivalent thresholds of target user groups for future innovative concept products. Similarly, Nagai and Georgiev (2011) constructed concept networks to investigate the deep impressions of artificial and natural materials, aiming to understand user tactile habits. Regarding material physical properties, Wastiels *et al.* (2012) conducted sensory evaluation experiments on ten types of stone with varying roughness and colors to study warmth perception. Their findings indicated that color changes had a greater impact on warmth perception than roughness variations, and that among stones of the same color, rougher surfaces were perceived as warmer. Klöcker *et al.* (2013) examined 12 different materials, identifying factors influencing pleasantness by measuring the normal and tangential force components and fingertip trajectories. They concluded that the average friction force generated by finger sliding and the surface topography were critical factors.

In summary, haptic research in related product fields focuses on the influence of product surfaces on tactile perception, establishing a hierarchical system of material physical properties, perception dimensions, and emotions. Sensory experiments measure data across various perception dimensions and emotions, linking these to specific physical properties of materials. This clarifies the relationship between material properties and human emotions, offering valuable references for material design and selection. However, given the complexity and ambiguity of human emotions, conventional regression analysis has limitations in addressing these mapping relationships. In an era of rapid advancements in artificial intelligence, the introduction of advanced algorithm models such as machine learning can more accurately capture and predict the complex relationships between materials and emotions, thereby enhancing the scientific rigor and effectiveness of design decisions.

Inspired by previous research in other fields, this study aims to contribute to a broader understanding of the tactile sensory experience in custom furniture design. By examining the hierarchical cognition of tactile sensations and integrating regression analysis with machine learning algorithms, this research seeks to develop a tactile evaluation model for custom wardrobe finishes. This model aims to quantitatively express users' subjective tactile feelings towards finishes and assist designers in understanding how touch influences consumer choices and satisfaction.

EXPERIMENTAL

Theoretical Framework Construction: Hierarchical Cognition of Tactile Sensation in Custom Wardrobe Finishes

Emotion is an important characteristic in the domain of psychological cognition, possessing multiple levels of attributes. In *Emotional Design*, Professor Donald Norman examines how design affects users' emotions and perceptions. He argues that design transcends functionality and holds significant emotional value. People's perceptions and reactions to products occur on three levels: visceral, behavioral, and reflective. The visceral level pertains to the sensory attributes of product design, such as color, texture, and smell. These elements constitute users' immediate perceptions when interacting with a product, instantly influencing their emotions and psychological state. The behavioral level centers on actual usage of the product, addressing its functionality, usability, comprehensibility, and the intuitiveness of user interactions. This level emphasizes the user's experience during product use, focusing on optimizing these experiences to fulfill users' needs and expectations. The reflective level concerns how a product reflects and shapes the user's personal and social identity. It focuses on users' reflections and evaluations after using the product, including their recollection of experiences and how these experiences affect their emotions and cognition. Success at this level relies on the product's ability to resonate with users' values, self-perception, and social expectations.

The tactile sensation of custom wardrobe finishes is an emotional experience perceived through the user's sense of touch. From a cognitive perspective, this experience is formed by first perceiving the external physical attributes of the finish through touch, which is influenced by the individual or combined effects of various physical properties.

Secondly, different physical properties lead to distinct emotional perceptions, described using adjectives. Finally, based on an individual's knowledge and experience, an overall emotional judgment is formed (Saxena *et al*. 2023). From a design thinking perspective, designers create layered designs based on the constraints of finish materials, textures, and processes under tactile conditions, as well as the cognitive characteristics and preferences of the target users. This approach aims to achieve a differentiated emotional experience for the product.

From the perspective of emotional design, the tactile sensation of custom wardrobe finishes can be conceptualized in three distinct levels. The visceral level pertains to the physical attributes of the finish's surface, serving as the foundational basis for tactile sensation. The behavioral level encompasses the multi-sensory perceptions users develop in response to these physical properties. The reflective level pertains to the comprehensive evaluations users form regarding the tactile sensation, influenced by personal preferences and past experiences. Consequently, the hierarchical perception of the tactile sensation of custom wardrobe finishes is delineated into three levels: the Physical Attributes Layer, the Tactile Sensation Layer, and the Comprehensive Evaluation Layer. The Physical Attributes Layer includes a set of surface physical properties affecting the tactile sensation of custom wardrobe finishes, such as roughness, thermal conductivity, coefficient of friction, and hardness. The Tactile Sensation Layer refers to the various tactile sensation adjectives formed by users under the influence of one or multiple physical properties, such as smooth, skin-friendly, and delicate. The Comprehensive Evaluation Layer is the comprehensive subjective judgement formed by users based on their life experiences, knowledge backgrounds, and preferences on various tactile emotional factors, such as satisfaction, surprise, and tolerance. The following experiments will be conducted based on the progressive relationship between the three levels (Fig. 1):

Experiment 1: Explore the relationship between the "Physical Attributes Layer" and the "Tactile Sensation Layer."

Experiment 2: Explore the relationship between the "Tactile Sensation Layer" and the "Comprehensive Evaluation Layer."

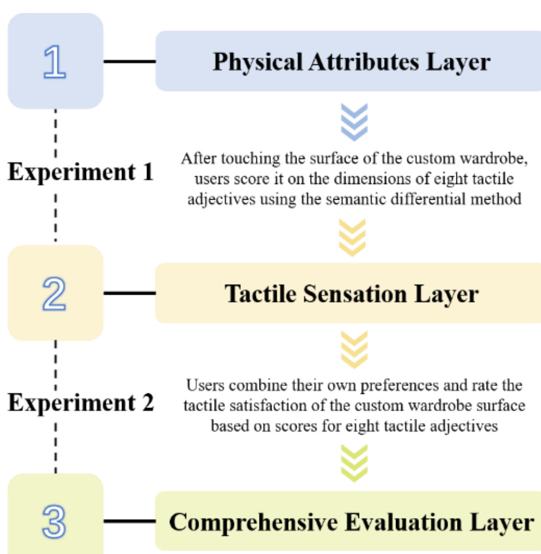

Fig. 1. Tactile evaluation model for the finish of custom wardrobes

Data Collection and Processing

Sample selection

In the domain of custom wardrobes, engineered wood is used as the base material, which is then surface-decorated with various veneering materials to offer products that are both stable, durable, and provide diverse tactile and visual experiences. This study conducted on-site research at the China (Guangzhou) International Building Decoration Fair, examining 189 products from 68 well-known domestic brands, including Sophia, Oppein, and Federal Gordon. Data were collected and categorized regarding the materials used for custom wardrobe finishes. The findings revealed that the mainstream materials in the market include melamine impregnated decorative paper, plastic film, and leather. Among these, plastic film was the most prevalent (42.9%), followed by melamine impregnated decorative paper (28.6%) and leather (15.3%). Based on these results, commonly used and widely found finishes in the custom wardrobe market were selected from these three mainstream materials as research samples, totaling 42 (including 20 plastic film finishes, 17 melamine impregnated decorative paper finishes, and 5 leather finishes). These samples were analyzed for their texture and tactile properties to provide data support for the subsequent development of a tactile perception evaluation model.

Measurement of the physical attributes layer

The tactile feel of custom wardrobe finishes is influenced by a variety of physical properties, including surface roughness, thermal conductivity, hardness, stickiness, moisture, and surface tension (Yanagisawa 2015). To identify the key physical properties affecting user tactile perception, a survey questionnaire utilizing a 5-point Likert scale was designed and administered for these six attributes. The questionnaire included the quantification of the impact of each attribute (where 1 indicates minimal impact and 5 indicates maximum impact). A total of 105 participants, all prospective consumers of custom wardrobes aged between 20 and 30, were invited to complete the questionnaire on-site. While rating the impact of each physical property, participants were allowed to randomly touch samples of custom wardrobe finish materials. The analysis of their ratings revealed that the top three physical properties influencing tactile sensation are surface roughness, thermal conductivity, and hardness. The following are the measurement methods for these three physical properties of custom wardrobe finishing materials used in this study.

Surface roughness refers to the unevenness of the processed surface, characterized by small spacing and minor peaks and valleys. This study measured the roughness data of finish samples using a 3D laser scanning profilometer. For rough surfaces, factors such as the height and distribution of micro-protrusions affect the skin's perception of roughness. The surface arithmetic mean height (S_a) and the profile line arithmetic mean deviation (R_a) are associated with the perception of roughness (Zhong *et al*. 2013). Therefore, this paper selects S_a and R_a as the characterization parameters for the surface profile height of finish samples, studying the surface roughness sensation related to texture height features. Moreover, influenced by the direction of the surface texture, R_a is further divided into measurements along the texture direction and perpendicular to the texture direction, named $R_{a\text{-}s}$ for along the texture direction and $R_{a\text{-}c}$ for perpendicular. This study also involves a detailed investigation of surface texture related to texture width characteristics, hence, the average width of profile elements (R_{sm}) is chosen as the characterization parameter for the width direction of the surface profile (Tang *et al*. 2021).

Thermal conductivity is a physical property of a material that describes its ability to conduct heat. Finish materials with high thermal conductivity can quickly transfer heat upon skin contact, resulting in a cold sensation. Measurement methods for thermal conductivity mainly include steady-state and transient methods. Since the sample materials in this study are all insulating materials with low thermal conductivity, the steady-state method was used for measurement (Kraemer and Chen 2014). The steady-state method, also known as the heat flow meter method, calculates the thermal conductivity by defining the heat flow density when the material is under constant heat source conditions and its internal temperature no longer changes with time.

Based on the national standard GB/T 1927.19-2021 "Test Methods for Physical and Mechanical Properties of Wood with Clear Small Defects," there is currently no standard method for measuring the hardness of engineered wood in China. Moreover, to exclude the influence of the engineered wood base material and measure only the finish veneering materials, the different types of sample finish materials—plastic, melamine-impregnated decorative paper, and leather—have different hardness measurement units, which cannot be converted between different units, making it impossible to measure the surface hardness of all samples with a single existing instrument. Therefore, this paper uses subjective sensory judgement by participants to indirectly obtain the hardness data of the samples (Tang *et al*. 2017). Subjective sensory judgement scores are typically obtained using a 7-point Likert scale. However, since participants' sensory judgements on the hardness of finish materials are ambiguous, this paper introduces fuzzy set theory to eliminate the ambiguity and subjectivity in sensory judgement (Sun *et al*. 2023). The relationship between linguistic variables is represented by triangular fuzzy numbers, converting linguistic variables into fuzzy numbers through scale transformation. The linguistic variables of scheme evaluation are converted into triangular fuzzy numbers, as shown in Table 1.

Table 1. Judgment Linguistic Variables and Triangular Fuzzy Number Correspondence

Judgment Scoring	Linguistic Variables	Triangular Fuzzy Numbers
1	Extremely Soft	(0,0,0.1)
2	Very Soft	(0,0.1,0.25)
3	Relatively Soft	(0.15,0.3,0.45)
4	Average	(0.35,0.5,0.65)
5	Relatively Hard	(0.55,0.7,0.85)
6	Very Hard	(0.75,0.9,1)
7	Extremely Hard	(0.9,1,1)

Assuming that *n* participants judge the hardness of *m* samples, their judgements can be considered as linguistic variables, transformed into triangular fuzzy number vectors, represented as:

$$Y_t^j = \left(\alpha_t^j, \beta_t^j, \sigma_t^j\right) \tag{1}$$

where $j = 1,2,\ldots,N$; $t = 1,2,\ldots,M$; Y_t^j is the triangular fuzzy number for the j participant's rating of the t sample; α_t^j is the lowest value of the triangular fuzzy number for the j participant on the t sample; β_t^j is the median value of the triangular fuzzy number for the j participant on the t sample; σ_t^j is the highest value of the triangular fuzzy number for the j participant on the t sample.

A triangular fuzzy number matrix for n participants against m samples is constructed, represented as:

$$Y = \begin{pmatrix} Y_1^1 & Y_1^2 & \cdots & Y_1^N \\ Y_2' & Y_2^2 & \cdots & Y_2^N \\ \cdots & \cdots & \cdots & \cdots \\ Y_M^1 & Y_M^2 & \cdots & Y_M^N \end{pmatrix} \tag{2}$$

If the judgment weight of the participants is denoted as φ_i, then the judgment weight vector of n participants will be represented as:

$$\varphi = (\varphi_1, \varphi_2, \cdots \varphi_N) \tag{3}$$

The fuzzy number set of n testers for the surface hardness of sample m is denoted as X_i, then:

$$X = (X_1, X_2, \cdots, X_m) \tag{4}$$

$$X_m = (\mu_m, \theta_m, \varepsilon_m) \tag{5}$$

$$\mu_m = \sum_{j=1}^{N} \alpha_t^j \cdot \varphi_j \tag{6}$$

$$\theta_m = \sum_{j=1}^{N} \beta_t^j \cdot \varphi_j \tag{7}$$

$$\varepsilon_m = \sum_{j=1}^{N} \sigma_t^j \cdot \varphi_j \tag{8}$$

$$X_m = \frac{(\mu_m + 2\theta_m + \varepsilon_m)}{4} \tag{9}$$

where X_m is the fuzzy value for the surface hardness of the m sample by N participants; μ_m is the sum of the lowest values of the fuzzy values for the m ample by N participants; θ_m is the sum of the median values of the fuzzy values for the m ample by N participants; ε_m is the sum of the highest values of the fuzzy values for the m ample by N participants. Ten designers with over five years of experience in the custom wardrobe field were invited as participants to judge and score the hardness of the sample finishes. Since the professional backgrounds of the ten participants were the same, their judgment weights for the samples are considered equal, that is, 1/10. The hardness values of the samples were calculated using the aforementioned formula.

Semantic quantification of the tactile sensation layer

Through literature review, web searches, and user interviews, a total of 53 emotion adjectives related to tactile sensations were identified (Chen and Chuang 2014). To ensure the efficiency of the experiment and the representativeness of the adjectives, the KJ method was used. The classification results of these 53 relevant terms were synthesized by a research team consisting of three professors in the field of furniture and seven master's students specializing in furniture studies, all from Nanjing, China. Synonyms and words with significant semantic deviations were removed. The team members then exchanged their screening results in pairs to further eliminate terms with low relevance. Ultimately, eight adjectives for describing tactile sensations in the tactile sensation layer were identified: smooth, clear, sharp, fine-grained, amusing, healing, elegant, and popular. The explanations of tactile adjectives are shown in Table 2.

Table 2. Explanations of Tactile Adjectives

Tactile Adjective	Semantic Explanation and Example
Smooth	Explanation: A smooth texture feels even to the touch, without any abrupt changes or harshness. It is soothing and comfortable, evoking a sense of calm and ease.
	Example: The polished surface of a wooden wardrobe door or the sleek finish of a glass cabinet panel.
Clear	Explanation: A clear texture is distinct and well-defined, with noticeable and easily recognizable features. It provides a sense of clarity and precision when touched.
	Example: The detailed carvings on a decorative wardrobe panel or the crisp, clean lines of a modern cabinet design.
Sharp	Explanation: A sharp texture has distinct and acute qualities that can be clearly felt. It often carries a sharp or cutting sensation at the raised edges of the texture. It can be slightly abrasive or pointed.
	Example: The sharp, distinct patterns on a faux stone veneer panel of a custom wardrobe or the textured ridges on an acrylic panel, where the edges of the ridges feel sharp to the touch.
Fine-grained	Explanation: A fine-grained texture feels intricate and refined, with subtle and detailed features. It is often associated with precision and quality.
	Example: The fine wood grain of a high-quality oak wardrobe.
Amusing	Explanation: An amusing texture has a whimsical and engaging quality, often with variations that surprise and amuse the touch. These textures can be regular or irregular, creating a sense of novelty and attraction.
	Example: The irregular, wavy patterns on a textured laminate surface or the varied, unpredictable bumps and grooves on a custom wardrobe panel designed to intrigue the touch.
Healing	Explanation: A healing texture is calming and comforting, often with a soft and gentle feel that promotes relaxation and well-being.
	Example: The gentle feel of a leather or fabric-upholstered wardrobe panel designed for comfort.
Elegant	Explanation: An elegant texture is sophisticated and refined, with a surface that conveys a sense of luxury and high quality. It exudes an atmosphere of grace and opulence.
	Example: The refined, luxurious feel of a velvet-upholstered panel on a wardrobe.
Popular	Explanation: A popular texture is familiar and widely appreciated, often found in everyday furniture. It is accessible and has a broad appeal.
	Example: The typical pine wood grain texture of laminate surfaces used in budget-friendly custom wardrobes, featuring straight or slightly wavy lines.

The Semantic Differential Method aggregates various scales into a numerical score to indicate the attitude levels of participants, with the grading scale typically being 5-point or 7-point. This study employed a 7-point scale to conduct a quantification experiment on tactile imagery words, involving 56 master’s students in furniture design as participants, including 28 males and 28 females. They were asked to sequentially assess the correlation between 6 physical properties and 8 tactile adjectives for 42 samples. Participants needed to rate each tactile adjective based on their feelings on the scale, ranging from 1 (strongly disagree) to 7 (strongly agree), to quantify their subjective sensations for each tactile description. To ensure the reliability and validity of the data, excluding external disturbances and the influence of other senses such as vision and hearing, participants conducted the experiment in a quiet, isolated space while wearing blindfolds and earplugs. Detailed instructions were given before the experiment to ensure that all participants could accurately understand the rating scale and the experimental procedure. In the semantic quantification experiment of tactile adjectives, the state of the samples actually touched by the participants is shown in Fig. 2. The scoring data from all participants were collected, and the quantified scores for the 8 tactile adjectives of the 42 samples were calculated.

Fig. 2. Participants touched the samples in the tactile adjective quantification experiment

Quantification of the comprehensive evaluation layer

Tactile sensations require a comprehensive emotional evaluation metric to accurately capture and reflect the emotional needs and overall experience of the target user group. This study used tactile satisfaction to express the comprehensive evaluation layer, as tactile satisfaction is directly linked to users' psychological feelings and emotional responses (Delong *et al*. 2012). It can comprehensively reflect the degree to which users accept the tactile characteristics of a product, their level of liking, and the strength of emotional connection. This satisfaction not only reflects the users' subjective evaluation but it can also objectively indicate the product's market acceptance and potential success rate. After completing the quantification experiment of tactile imagery words, the evaluation of tactile satisfaction in the comprehensive evaluation layer is conducted using a 7-point scale, with scores ranging from 1 to 7, where 1 represents the least liked and 7 represents the most liked. Other experimental environment and process requirements are the same as those described in the previous experiment. The scoring data from all participants are collected and the tactile satisfaction scores for the 42 samples are calculated.

Model Establishment

Mapping model construction between "physical attributes layer" and "tactile sensation layer"

In subsequent Experiment 1, it was found that the relationship between the "Physical Attributes Layer" and the "Tactile Sensation Layer" was nonlinear. To address this issue, a BP (Backpropagation) neural network was introduced. A BP neural network is a type of multilayer feedforward neural network, characterized by its core feature of training through the backpropagation algorithm. This effectively updates the weights and biases within the network to minimize the network's prediction error, thus achieving the ability to solve nonlinear problems (Zhao *et al*. 2012). The BP neural network model used in this paper was developed and coded in Matlab R2022a software. It collects experimental data from custom wardrobe finish samples and sets the input layer as the 42 samples'

Surface Arithmetic Mean Height (S_a), Profile Line Arithmetic Mean Deviation perpendicular to the grain ($R_{a\text{-}c}$), Profile Line Arithmetic Mean Deviation along the grain ($R_{a\text{-}s}$), Average Width of Profile Elements (R_{sm}), Thermal Conductivity, and Surface Hardness. The output layer is the semantic scoring of eight tactile adjectives: smooth, clear, sharp, fine-grained, engaging, soothing, elegant, and popular, utilizing a three-layer BP neural network model with a single hidden layer. The performance and accuracy of the BP neural network largely depends on the setting of its parameters, including data normalization, the loss function, the number of neurons in the hidden layer, the training function, and the activation function. To accurately predict the semantic scoring of the tactile adjectives for custom wardrobe finish samples, data from 42 samples were randomly extracted, with data from 30 samples used as the training set, data from 6 samples as the validation set, and data from the remaining 6 samples as the test set. This approach tests and selects the most suitable number of neurons in the hidden layer, training function, and activation function, thereby optimizing the BP neural network model.

Due to the different dimensions of S_a, $R_{a\text{-}c}$, $R_{a\text{-}s}$, R_{sm}, Thermal Conductivity, and Surface Hardness, untreated raw data often contain different magnitudes and dimensions, which may lead to unstable gradients during the training process or even affect the convergence of the model. Normalization scales the values in the original data to a uniform range, improving training efficiency and prediction accuracy (Singh and Singh 2020). In this study, the most common method of linear normalization was used, which scales the data to a range of [0,1] through linear transformation. The normalization formula is:

$$x_{\text{norm}} = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{10}$$

Here, x_{norm} represents the normalized data, x represents the original data, and $\min(x)$ and $\max(x)$ are the minimum and maximum values in that feature column, respectively.

The loss function serves as a criterion to measure the difference between the network's predicted values and actual values, playing a crucial role in guiding the training process (Popoola *et al*. 2019). Considering that the objective of this study is to predict the semantic scoring of tactile adjectives, which is a regression problem, the Mean Squared Error (MSE) was chosen as the loss function. The calculation formula for MSE is:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(y_{\text{pred},i} - y_{\text{true},i}\right)^2 \tag{11}$$

where $y_{\text{pred},i}$ represents the model's predicted output, $y_{\text{true},i}$ represents the true value, and n represents the number of samples.

MSE quantifies the size of the error between predicted and actual values. Its optimization goal is clear and intuitive, facilitating the updating and optimization of weights through the backpropagation algorithm. Moreover, the continuity and differentiability of MSE in its mathematical properties ensure stability and efficiency in optimization algorithms.

The selection of the number of neurons in the hidden layer essentially seeks a balance to ensure that the network can capture complex data patterns without overfitting due to excessive model complexity (Qiao and Sun 2013). Too many neurons can enhance the model's representation ability but may lead to excellent performance on training data with poor generalization on new data; conversely, too few neurons might result in the model's inability to fully learn the patterns in the data, leading to underfitting. In practice, an experimental approach is often used to gradually adjust the number of neurons, monitoring the model's performance on an independent validation set through techniques such as cross-validation to guide the adjustment of neuron numbers. Therefore, when setting the number of neurons in the hidden layer of the BP neural network, empirical formulas and experimental methods were used to determine the optimal number of neurons. The commonly used empirical formula is as follows,

$$r = \sqrt{l + k} + u \quad (12)$$

where r is the number of neurons in the hidden layer, l is the number of nodes in the input layer, k is the number of nodes in the output layer, and u is a constant between 1 and 10. Using this formula, the initial estimate for the number of neurons was calculated to be a constant between 4 and 13.

The initially estimated number of neurons was sequentially inputted into the BP neural network for simulation. During the iterative process, the code constructed neural networks with varying numbers of neurons in the hidden layer and trained them. By calculating the performance of each network on the validation set and comparing it with the previous minimum MSE, the code dynamically updated and recorded the best number of neurons in the hidden layer and the corresponding minimum MSE, with results shown in Fig. 3. When the number of neurons increased from 4 to 7, the Mean Squared Error (MSE) dropped sharply, indicating a significant improvement in model performance. At 7 neurons, the model reached a local minimum of MSE, after which there was a slight increase in error. Considering the overall trend, this might indicate that the current network structure did not significantly improve performance with an increased number of neurons. As the number of neurons in the hidden layer increased to 10, a noticeable downward trend appeared in the graph, and the model's MSE reached its lowest point. Thereafter, as the number of neurons continued to increase, the MSE consistently rose, thereby determining that the model's performance was optimized when the number of neurons in the hidden layer was set to 10.

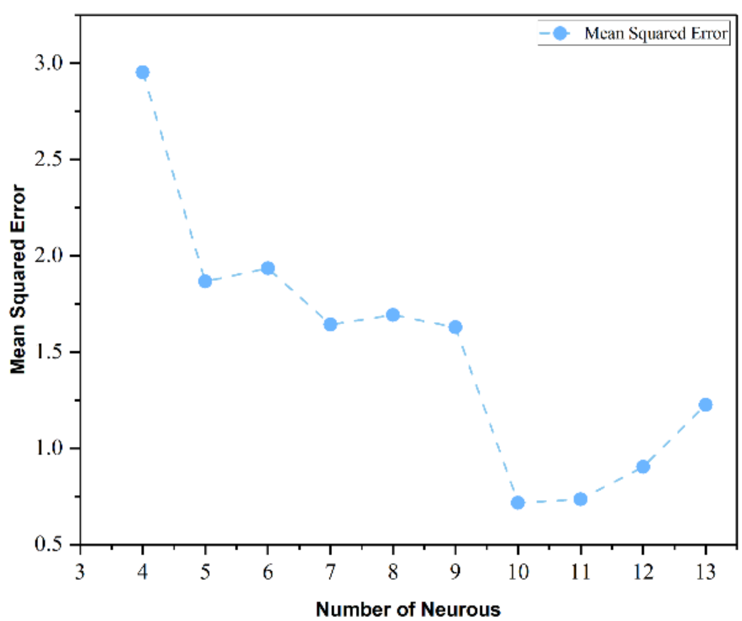

Fig. 3. Performance of models with different numbers of neurons in the hidden layer

A set of candidate training functions was established, covering a wide range of algorithms including the Levenberg-Marquardt algorithm (trainlm), BFGS quasi-Newton method (trainbfg), and conjugate gradient descent method (trainscg), to encompass a broad spectrum of network training strategies (Sadeghi 2000). In the selection process of training functions, this study employed an iterative approach in which each candidate training function was applied to the same BP neural network structure, which had been configured based on the optimal number of nodes in the hidden layer determined from previous experiments. The data segmentation strategy for the network was set to random division, with 70% of the data used for training and the remaining 30% evenly distributed between validation and test sets, ensuring fairness and comprehensiveness in model evaluation. In each iteration, the network was trained using the current training function with a maximum of 1000 training iterations, followed by performance evaluation on the validation set. MSE was used as the performance metric, aiming to quantify the difference between model predictions and actual target values, with results shown in Fig. 4. The results in the figure show significant fluctuations in MSE across different training functions, indicating that the choice of training function has a significant impact on model performance. The MSE value corresponding to the Levenberg-Marquardt algorithm (trainlm) was the lowest, indicating it had the best performance among the set of training functions. The minimum error indicates that this algorithm produced the smallest difference between predictions and actual values on the validation set, making it the optimal choice among the experiments conducted.

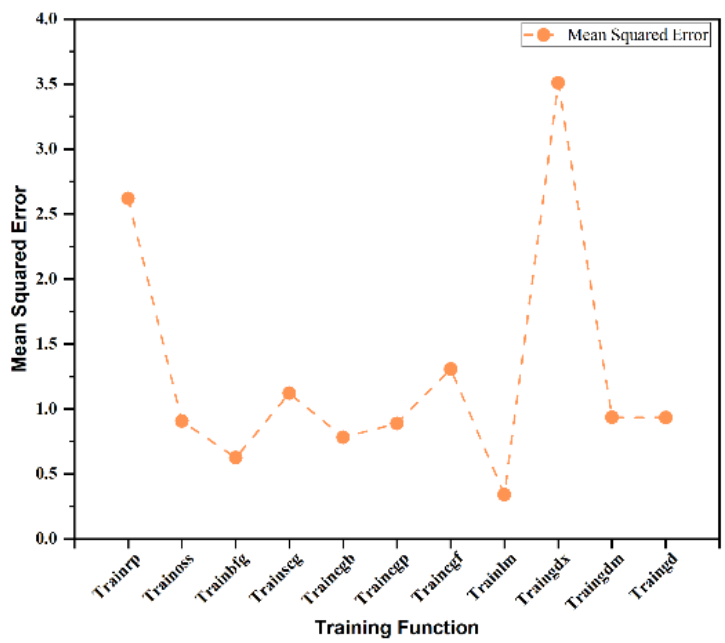

Fig. 4. The relationship between different training functions and model mean squared error

In the process of constructing a neural network, selecting the appropriate activation function is crucial, as it directly affects the network's ability to handle nonlinear problems (Pan *et al*. 2020). To determine the best combination of activation functions, this study conducted experimental evaluations on the BP neural network using different combinations of activation functions. Four commonly used activation functions were selected, including two saturating functions (tansig and logsig) and two non-saturating functions (purelin and ReLU). Initially, each of these functions was paired with itself to form a set of activation functions for the input and output layers. Secondly, since the semantic scoring values of tactile adjectives do not require dimension normalization, the impact of the two linear functions on the accuracy of the neural network was specifically tested in the output layer. The output range of the purelin function is from negative infinity to positive infinity, while the output range of the ReLU function is from zero to positive infinity. Given that the semantic scoring values for tactile adjectives are all positive, it was sufficient to test only one of these, and for this study, the purelin function was chosen as the activation function for the output layer and paired with the remaining three for the input layer for testing.

Experiments were conducted on the BP neural network with different activation function configurations to evaluate their performance on specific tasks. In the experiments, each network formed by a combination of activation functions underwent a complete training cycle, with the maximum number of training iterations set to 1000. Mean Squared Error (MSE) was used as the performance metric to evaluate the accuracy of the model's predictions. After the training was completed, performance metrics were calculated on the validation dataset. The results are shown in Fig. 5.

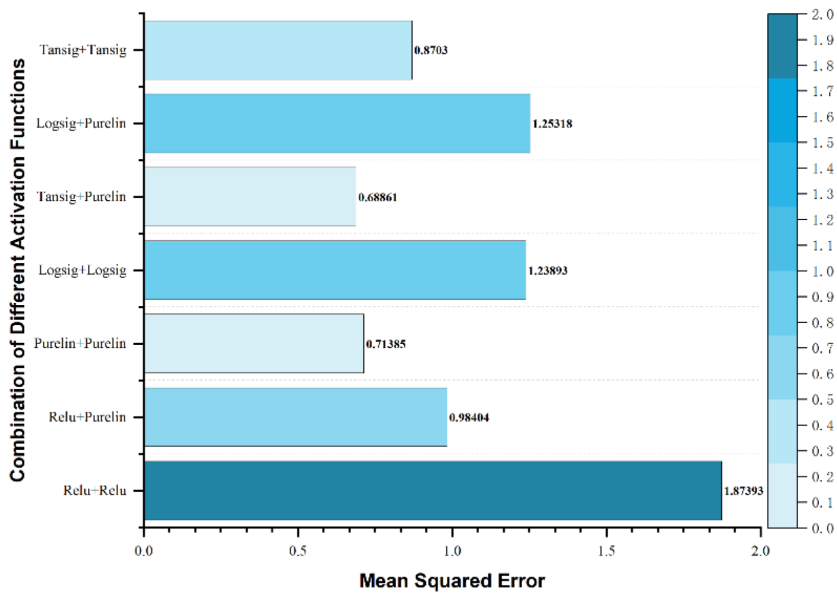

Fig. 5. The impact of different activation function combinations on model mean squared error

The MSE of the Tansig+Purelin combination was the lowest (approximately 0.68861), indicating that this combination provided the best performance under the current experimental setup. The advantage of using the tansig function as the activation function for the input layer lies in its non-linear characteristics, enabling the network to effectively capture and learn complex data relationships. Additionally, the relatively smooth derivative of the hyperbolic tangent function helps to avoid the vanishing gradient problem, ensuring the effective transmission of gradient information during the training of deep networks. Applying the purelin function to the output layer simplifies the learning process and accelerates network training, making the final model's output more directly reflect the transformation results from the input layer to the hidden layer. It provides a flexible output range for the network, especially suitable for regression tasks. Therefore, the Tansig function is chosen as the activation function for the input layer, and the Purelin function is selected for the output layer.

In summary, the neural network's input layer consists of parameters of 6 physical properties for 42 samples, and the output layer consists of the quantified scores of these samples on 8 tactile adjectives. The hidden layer has one layer with 10 neurons. The activation function for the input layer is the Tansig function, and the activation function for the output layer is the Purelin function. The training function is trainlm, with Mean Squared Error used as the loss function, and the maximum number of training iterations is capped at 1000. This setup constructs a mapping model between the "Physical Attributes Layer" and the "Tactile Sensation Layer" based on the BP neural network.

Mapping model construction between " tactile sensation layer " and " comprehensive evaluation layer "

In exploring the intrinsic connection between the “Tactile Sensation Layer” and the “Comprehensive Evaluation Layer,” the tactile satisfaction scores obtained from the comprehensive evaluation layer of 42 samples were selected as the dependent variable S. The scores of the eight tactile adjectives—smooth (h1), clear (h2), sharp (h3), fine-grained (h4), amusing (h5), healing (h6), elegant (h7), and popular (h8)—were used as independent variables. These were imported into SPSS Statistics 27 software for correlation analysis. Combined with multiple linear regression, a mapping relationship model between the two was established to facilitate the prediction of tactile satisfaction.

RESULTS AND DISCUSSION

Experiment 1 "Physical Attributes Layer-Tactile Sensation Layer"

Linear regression analysis

To analyze the relationship between the Physical Attributes Layer and the Tactile Sensation Layer, the correlation coefficients between the parameters of various physical properties and the semantic scores of tactile adjectives, as well as the determination coefficients in regression analysis, were calculated. This helps reveal whether there is a correlation and linear relationship between them. The parameters of 6 physical properties from the Physical Attributes Layer of 42 samples were used as independent variables, and the semantic scoring of 8 tactile adjectives were used as dependent variables. All data were imported into SPSS Statistics 27 software for Pearson correlation analysis and regression analysis, resulting in Table 3.

Table 3. Correlation Coefficients and Determination Coefficients between Each Physical Property and Tactile Adjectives

Tactile Adjective	Pearson Correlation Coefficient						R^2
	S_a	$R_{a\text{-}c}$	$R_{a\text{-}s}$	R_{sm}	Thermal Conductivity	Surface Hardness	
Smooth	-0.712**	-0.752**	-0.628**	-0.605**	0.229	-0.290	0.741
Clear	0.336*	0.358*	0.215	0.323*	0.214	0.113	0.133
Sharp	0.584**	0.633**	0.477**	0.373*	-0.224	0.494**	0.717
Fine-grained	-0.669**	-0.714**	-0.554**	-0.526**	0.240	-0.402**	0.744
Amusing	0.640**	0.670**	0.517**	0.557**	0.119	0.100	0.467
Healing	-0.364*	-0.412**	-0.390*	-0.302*	0.315*	-0.522**	0.377
Elegant	-0.323*	-0.379*	-0.378*	-0.343*	0.347*	-0.490**	0.494
Popular	-0.701**	-0.724**	-0.650**	-0.655**	0.313*	0.349*	0.442
Notes：*p<0.05 **p<0.01							

The Pearson correlation results indicate that, overall, there was a general correlation between the six physical properties and the eight tactile adjectives, with S_a, $R_{a\text{-}c}$, and R_{sm} showing significant correlations with all eight tactile adjectives. $R_{a\text{-}s}$ showed significant correlation with Smooth, Sharp, Fine-grained, Amusing, Healing, Elegant, and Popular; Thermal Conductivity with Healing, Elegant, and Popular; and Surface Hardness with Sharp, Fine-grained, Healing, Elegant, and Popular. While other correlations were apparent, they were weaker. Considering the comprehensive impact of the physical properties on the semantic scoring of the tactile adjectives, these weaker correlations should not be overlooked.

The results of the linear regression analysis show that the adjectives Fine-grained, Smooth, and Sharp had a good fit with the six physical properties, with determination coefficients (R^2) all greater than 0.5. The determination coefficients for the rest were less than 0.5, indicating that fitting the relationship between the "Physical Attributes Layer" and the "Tactile Sensation Layer" using a linear regression equation was not ideal. It must be recognized that descriptions of tactile sensations and semantic scoring by users are often vague and complex. The nature of these evaluations not only includes varying personal preferences but also reflects a wide range of cultural and emotional factors, which often interact in a nonlinear manner. Traditional linear regression models are inadequate in this context because they typically can only capture linear relationships between variables and fail to effectively model the underlying complex and ambiguous structures. Therefore, this study employed a BP neural network model to fully capture and analyze nonlinear relationships, accurately depicting the dynamic link between the "Physical Attributes Layer" and the "Tactile Sensation Layer."

Training Results and Analysis of the BP Neural Network Model

To accurately predict the quantification values of tactile adjectives for typical samples of custom wardrobe finishes, a random sampling method was used to segment the 42 typical samples during the initial phase of model development. This data segmentation method ensures the independence of the training, validation, and test datasets, thereby enhancing the persuasiveness and scientific rigor of the model evaluation results. Additionally, random segmentation of the samples helps reduce data selection bias and improves the reliability of the model's prediction results. The fitting performance of the mapping model between the "physical parameter layer" and the "tactile sensation layer" is shown in Fig. 6.

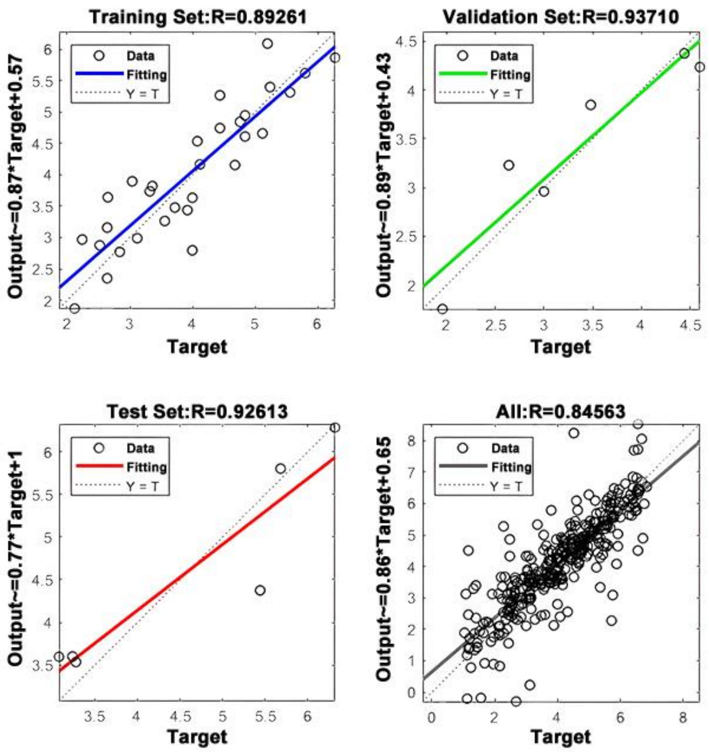

Fig. 6. The fitting effect of the BP neural network

The correlation coefficient R measures the fit of the mapping model, indicating the linear correlation between the model's predicted values and the actual values. When R is close to 1, it means that the predicted values are highly correlated with the actual values, indicating that the model fits the data well. Conversely, when R is close to 0, it indicates a weak linear relationship between the predicted and actual values, implying a low fit. The results shown in the figure demonstrate a high degree of consistency and accuracy in the predictive performance of the mapping model between the "physical parameter layer" and the "tactile sensation layer" across the training, validation, and test sets. The correlation coefficient R between the predicted and actual values was 0.89261 for the training set, 0.93710 for the validation set, and 0.92613 for the test set. In the scatter plots of each dataset, data points were evenly distributed on both sides of the fitted line. Additionally, the dashed line Y=T represents a perfect match between predicted and actual values, and the smaller the deviation of the fitted line from this dashed line, the more accurate the model's predictions. In summary, the model's performance across the datasets demonstrates its effectiveness in predicting the quantification values of tactile adjectives for custom wardrobe finishes.

BP Neural Network Model Performance Validation

After the parameters of the BP neural network model were determined and training was completed, an independent validation set was used to validate the model, to evaluate its generalization ability and prediction accuracy. This validation set consists of samples that did not participate in the training process, selected to cover the entire range of materials to ensure comprehensive validation. Fourteen new samples were collected for validation of the neural network model, measuring the physical parameters of the 6 properties in the

Physical Attributes Layer for these samples. Thirty master's students specializing in furniture design, including 15 males and 15 females, were invited as participants. They used the semantic quantification method for the Tactile Sensation Layer mentioned in the research method to obtain the semantic scores for the 6 physical properties of the 14 new samples on the 8 tactile adjectives. The physical parameters of the 6 properties and the semantic quantification values of the tactile adjectives were input into the input and output layers of the trained BP neural network, respectively. The network model then performed forward propagation on the input data to obtain the predicted values of the emotional scores.

In this study, a backpropagation neural network model was utilized to map the six physical property parameters of custom wardrobe finishes to the semantic quantification values of eight tactile adjectives, exploring the quantitative relationship between physical properties and sensory experiences. After initial training with 42 samples, the model was further validated on 14 new samples. Furthermore, the BP neural network predicted the semantic scores of the 14 new samples on the eight tactile adjectives. The relationship between predicted and actual values was visualized through line graphs, with each tactile adjective represented by a graph, as shown in Figs. 7 and 8. By calculating the Mean Squared Error (MSE) and determination coefficient (R^2) for each tactile description, the model's performance on each semantic node was evaluated.

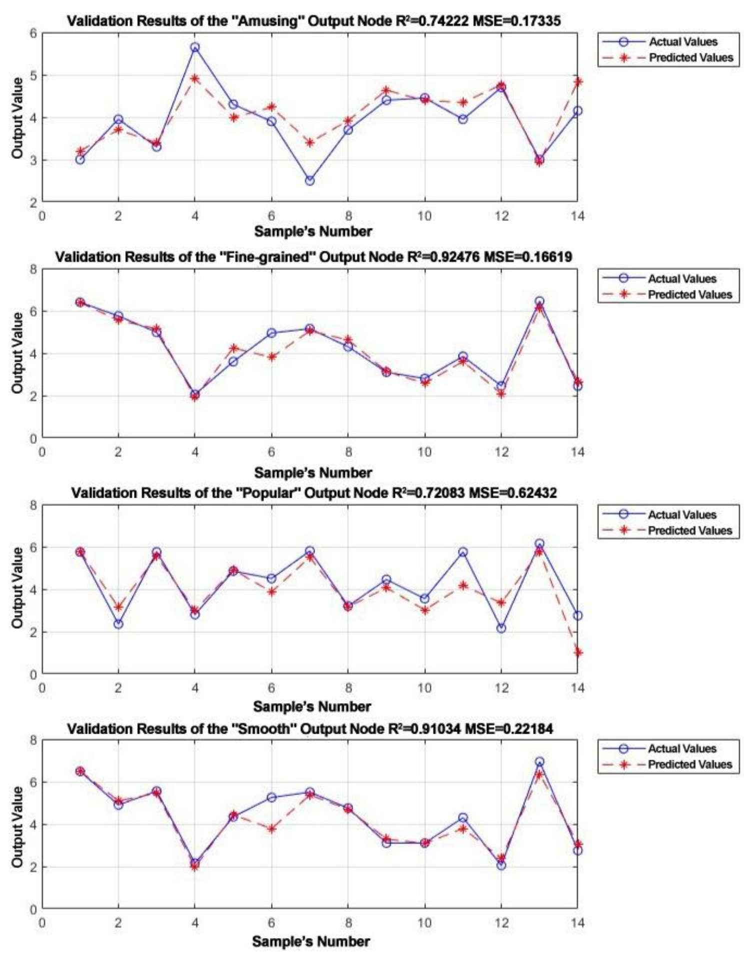

Fig. 7. Line graph of the predicted and actual values for the nodes "amusing," "fine-grained," "popular," and " smooth"

The analysis results show that the determination coefficients (R^2) were all greater than 0.72, exhibiting a performance level higher than traditional linear regression analysis across the tactile adjective nodes. This demonstrates the BP neural network's effectiveness in capturing complex nonlinear relationships and significantly enhancing prediction outcomes. Specifically, the determination coefficients (R^2) for "Fine-grained," "Healing," and "Smooth" nodes were all above 0.9, reflecting the model's high accuracy and reliability in predicting these three tactile descriptions. Meanwhile, for the "Clear," "Sharp," and "Elegant" nodes, with determination coefficients (R^2) all above 0.8, it indicates the neural network's precise capture of the associations between physical properties and tactile adjectives. The determination coefficients for "Amusing" and "Popular" were lower, at R^2=0.74222 and R^2=0.72083, respectively, likely due to the higher ambiguity of the corresponding tactile descriptions. Such ambiguity might stem from semantic polysemy or subjective sensory differences, making the relationship between these two tactile descriptions and physical properties less clear than others. Although the "Popular" node had the highest MSE value, the mean error of 0.211 on a 7-point scale rating had a minimal impact and the prediction trend generally aligns with the actual observational data, indicating that this error level is acceptable in tactile assessment.

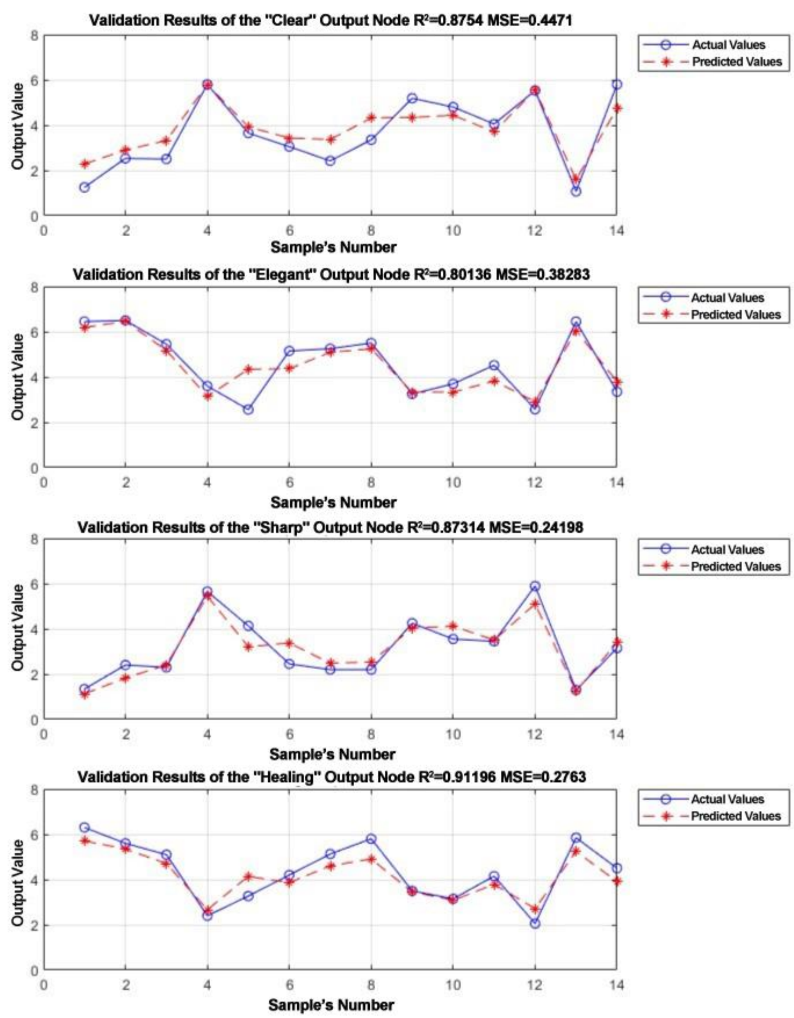

Fig. 8. Line graph of the predicted and actual values for the nodes "clear," "elegant," "sharp," and "healing"

Experiment 2 "Tactile Sensation Layer-Comprehensive Evaluation Layer"

Data results and analysis

The Pearson correlation results are presented in Table 4. Satisfaction had a correlation coefficient of -0.360 with “Amusing,” indicating a significant negative correlation between the two, which was validated at the 0.05 significance level. Additionally, satisfaction showed strong positive correlations with “Fine-grained” (correlation coefficient of 0.688), “Popular” (correlation coefficient of 0.535), “Smooth” (correlation coefficient of 0.646), “Elegant” (correlation coefficient of 0.739), and “Healing” (correlation coefficient of 0.744), and these correlations were confirmed at the 0.01 significance level. This means that as the tactile experiences of “Fine-grained,” “Popular,” “Smooth,” “Elegant,” and “Healing” increase, satisfaction correspondingly improves. Conversely, satisfaction showed significant negative correlations with “Clear” (correlation coefficient of -0.403) and “Sharp” (correlation coefficient of -0.766), also confirmed at the 0.01 significance level, indicating that the enhancement of these tactile experiences led to a decrease in satisfaction.

Subsequently, a multiple linear regression analysis was conducted. The results showed that the model’s determination coefficient R^2 was 0.765, indicating that the eight tactile adjectives were able to explain the variation in tactile satisfaction. An F-test was performed on the model ($F=13.437$, $p<0.05$), indicating that the eight tactile adjectives had an impact on tactile satisfaction. However, the presence of Variance Inflation Factor (VIF) values greater than 10 in the model suggests the existence of collinearity issues, meaning there were certain correlations among the independent variables in the model. To address the impact of collinearity on the model, it is necessary to first conduct a principal component analysis (PCA) on the eight tactile adjectives, followed by a linear regression analysis of the component scores and tactile satisfaction.

Table 4. Pearson Correlation Coefficients between Tactile Adjectives and Satisfaction

Tactile Adjectives	Satisfaction
Smooth	0.646**
Clear	-0.403**
Sharp	-0.766**
Fine-grained	0.688**
Amusing	-0.360*
Healing	0.744**
Elegant	0.739**
Popular	0.535**

The scores of the eight tactile adjectives were imported into SPSS for principal component analysis. The Bartlett’s test of sphericity results showed $KMO=0.877>0.6$ and $p<0.05$, indicating that the data were suitable for principal component analysis. The analysis yielded variance explained by the tactile adjectives, extracting 2 principal components. Principal component 1 explained 77.889% of the variance, and principal component 2 explained 12.122%, with a cumulative explanation rate exceeding 90%. The loadings and linear combination coefficients matrix of the eight tactile adjectives were calculated, as shown in Table 5.

Table 5. Factor Loadings and Linear Combination Coefficients for Tactile Adjectives

Tactile Adjectives	Factor loadings		Communality	Linear Combination Coefficients		Composite Score Coefficient
	Principal Component 1	Principal Component 2		Principal Component 1	Principal Component 2	
Smooth	0.974	-0.064	0.953	0.390	-0.065	0.347
Clear	-0.943	0.130	0.906	-0.378	0.132	0.345
Sharp	-0.964	-0.143	0.951	-0.386	-0.145	0.354
Fine-grained	0.981	0.045	0.964	0.393	0.045	0.346
Amusing	-0.752	0.500	0.816	-0.301	0.508	0.329
Healing	0.810	0.486	0.892	0.324	0.493	0.347
Elegant	0.855	0.425	0.912	0.342	0.432	0.355
Popular	0.741	-0.509	0.808	0.297	-0.517	0.326
Weights	0.865	0.135	—	0.865	0.135	—

From Table 5, which shows the loading coefficients of the tactile adjectives, it is clear that the communalities for all eight tactile adjectives were higher than 0.4. Thus, there was a strong association between each adjective and the principal components, indicating that the two principal components can effectively extract information. The relationship equation between the principal components and each tactile adjective can be established using the linear combination coefficients. Component 1 = 0.390h1 - 0.378h2 - 0.386h3 + 0.393h4 - 0.301h5 + 0.324h6 + 0.342h7 + 0.297h8; Component 2 = -0.065h1 + 0.132h2 - 0.145h3 + 0.045h4 + 0.508h5 + 0.493h6 + 0.432h7 - 0.517h8. The composite score = 0.865Component 1 + 0.135Component 2.

Using the composite score from the principal component analysis as the independent variable and the tactile satisfaction scores as the dependent variable for correlation analysis, the model R^2 was 0.604. An F-test on the model ($F=60.900$, $p<0.05$) indicates that the composite score from the principal component analysis had an impact on tactile satisfaction, with a regression coefficient of 0.167 ($t=7.804$, $p<0.01$) and an intercept of 3.720, indicating a significant positive correlation between the composite score of principal component analysis and tactile satisfaction. Furthermore, by observing the cumulative probability plot of the standardized residuals of the regression model, as shown in Fig. 9, it is apparent that the deviation between the model's predicted values and the actual observed values is minimal, implying no significant differences compared to a standard normal distribution. Analyzing the scatter plot of standardized predicted values against standardized residuals, as can be seen in Fig. 10, as the standardized predicted values increased, the residuals fluctuated within a range of positive and negative 2, without any systematic changes as the predicted values increase, indicating constant variance of residuals, or homoscedasticity.

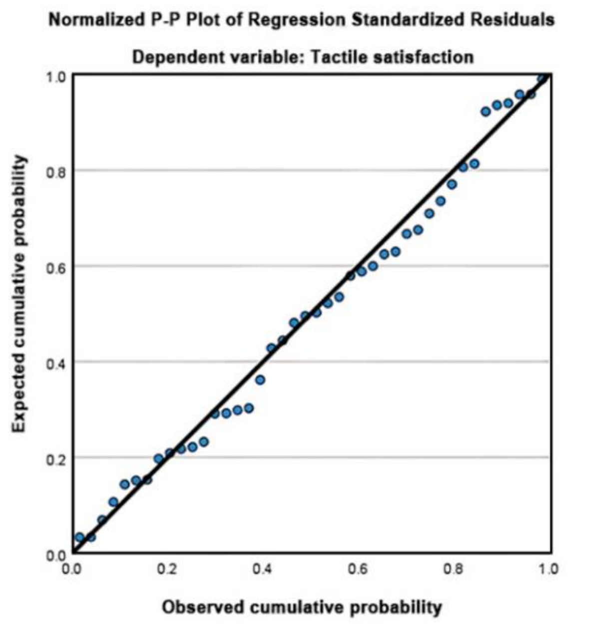

Fig. 9. Cumulative probability plot of standardized residuals

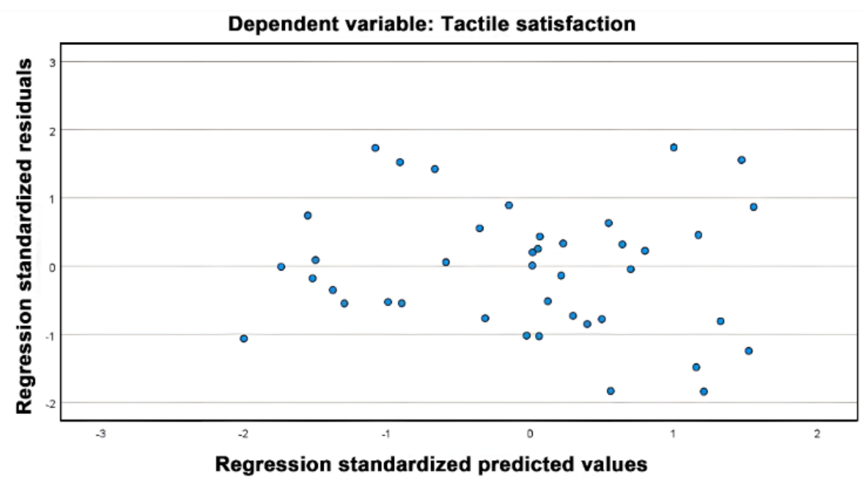

Fig. 10. Regression prediction scatter plot

Based on these observations, the fit of this regression model was judged to be acceptable, as it demonstrated good predictive consistency and stable error variability. The final multiple linear regression equation was: S = 3.720 + 0.055h1 - 0.052h2 - 0.059h3 + 0.058h4 - 0.032h5 + 0.058h6 + 0.059h7 + 0.031h8. From the equation, it is evident that tactile satisfaction was positively correlated with “Smooth,” “Fine-grained,” “Healing,” “Elegant,” and “Popular,” and negatively correlated with “Clear,” “Sharp,” and “Amusing.” This indicates that users prefer custom wardrobe finishes with subtle surface textures, a Fine-grained touch, and common appeal. Such finishes can provide emotional value, relieve stress, and align with the functional tone of bedroom spaces.

Evaluation Model for Tactile Sensations of Custom Wardrobe Finishes

By integrating physical experimental measurements with subjective quantification methods, data samples were obtained for each layer. To investigate the mapping relationship between the “Physical Attributes Layer” and the “Tactile Sensation Layer,” a

BP neural network was employed. This approach addressed the issue of low determination coefficients in multiple linear regression equations, which had previously hindered the precise prediction of quantitative values for tactile adjectives. Consequently, a mapping model based on the BP neural network was developed to capture the nonlinear relationship between the "Physical Attributes Layer" and the "Tactile Sensation Layer." This model predicts the quantitative values of target tactile adjectives based on the physical parameters of various design elements of custom wardrobe finishes. For the relationship between the "Tactile Sensation Layer" and the "Comprehensive Evaluation Layer," a multiple linear regression equation was utilized to establish a correlation model, enabling the prediction of user satisfaction with tactile sensations based on the quantitative values of target tactile adjectives. The combination of the BP neural network and multiple linear regression equations resulted in a hierarchical prediction pathway for evaluating tactile sensations of custom wardrobe finishes, spanning from the "Physical Attributes Layer" to the "Tactile Sensation Layer" and finally to the "Comprehensive Evaluation Layer." This evaluation model is depicted in Fig. 11.

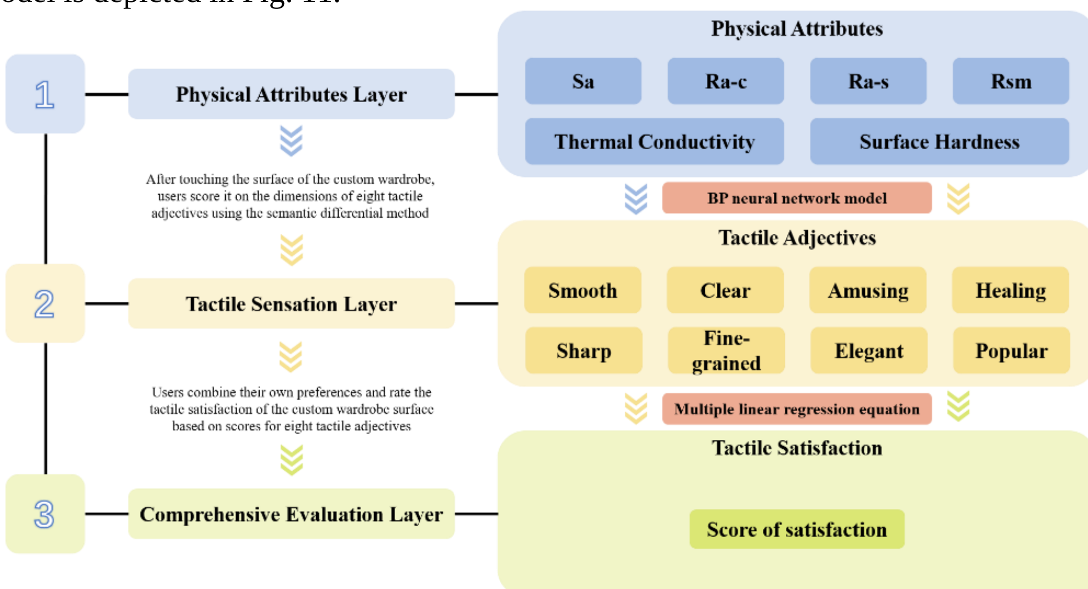

Fig. 11. Tactile evaluation model for custom wardrobe finishes

Utilizing this model, designers can predict the quantitative values of target tactile adjectives for new finishes based on the physical parameters of custom wardrobe design elements. This capability assists designers in understanding target users' tactile perceptions of new finishes and in predicting their satisfaction with the tactile sensations, thereby guiding subsequent design work.

DISCUSSION

Academic Significance

This study addresses a critical research gap by constructing a tactile evaluation model for custom wardrobe finishes in China, thereby enriching the existing theoretical foundation. From an interdisciplinary perspective, the research integrates tactile perception theory from psychology, physical attribute measurement from materials science, and BP neural network modeling from computer science, comprehensively exploring various aspects of tactile evaluation. This cross-disciplinary approach enhances both the comprehensiveness and depth of the study, providing new research ideas and methods for researchers in related fields and promoting knowledge integration and innovation across disciplines. The tactile evaluation model developed in this study has practical value not only in the design of custom wardrobes but also in other furniture domains, such as custom panel furniture and solid wood furniture, demonstrating its broad applicability and potential for widespread adoption. Furthermore, the methods and findings of this research offer important references and insights for subsequent studies.

Future research can refine and expand the tactile evaluation model by exploring larger sample sizes, more diverse physical attributes, and a wider range of tactile sensations. Subsequent studies could also investigate the model's applicability in different cultural contexts and enhance its predictive accuracy and usability by integrating virtual reality technology and artificial intelligence algorithms, thereby advancing the field of tactile evaluation. In summary, the tactile evaluation model constructed in this study not only fills a gap in the evaluation of tactile sensations for custom wardrobe finishes but also enhances research comprehensiveness and depth through an interdisciplinary approach. The model shows broad applicability and potential for adoption in the design of custom wardrobes and other furniture domains. The study's findings provide a crucial reference for future work, and the integration of emerging technologies will further promote the development of the tactile evaluation field.

Academic Significance

The tactile evaluation model developed in this study holds significant practical applications and relevance in three primary areas: product design optimization, capturing user needs, and market positioning and promotion.

Firstly, for product design optimization, the model enables designers to predict the tactile effects of various materials and surface treatments in advance. This capability allows for optimized material selection during the design phase, reducing trial-and-error costs and shortening the design iteration cycle, thereby improving design efficiency and accuracy. The model offers a data-driven approach for scientifically adjusting surface treatment processes, including parameters such as surface roughness, thermal conductivity, and hardness, to achieve optimal tactile experiences. Additionally, the model can be applied to personalized design customization, allowing designers to use quantified tactile data to tailor products to individual tactile preferences, meeting specific user needs. This data-driven approach to personalized design enhances product quality and user satisfaction, boosting market competitiveness.

In addition, the model aids designers in understanding users' implicit needs and tactile preferences by quantifying their emotional responses to touch. Integrating user feedback into the design process creates a positive feedback loop between user needs and design improvements. The model's data-driven method ensures precise capture and analysis of user requirements, allowing designers to adjust and optimize based on actual user feedback, thus enhancing the product's user experience. By accurately capturing and responding to users' tactile needs, designers can create products that are not only highly functional but also emotionally satisfying, thereby increasing user satisfaction.

Lastly, enterprises can utilize the model's predictive data to identify user groups with different tactile preferences, facilitating precise market segmentation. This accurate market positioning helps companies develop products tailored specifically to target user groups, increasing market penetration and share. For marketing strategy, companies can leverage the data provided by the model to design more appealing marketing campaigns. By highlighting the unique tactile experiences of their products, companies can attract more potential customers and enhance brand awareness and market influence. The tactile evaluation model also provides new avenues for differentiation in a highly competitive market. Currently, the custom wardrobe market suffers from product homogenization. Enterprises and designers can use the model's data to innovate from the perspective of touch and tactile sensation, helping them stand out in a competitive market, achieve differentiated competition, and enhance brand uniqueness and market appeal.

In summary, the tactile evaluation model developed in this study exhibits significant application value in optimizing product design, capturing user needs, and market positioning and promotion. Despite the notable achievements of this research, limitations such as the sample size may impact the model's generalizability. Future research can enhance the model's accuracy and applicability by expanding the sample set, exploring alternative neural network structures, and incorporating additional physical parameters related to tactile sensations. Furthermore, integrating genetic algorithms, deep learning algorithms, or virtual reality technology could bolster the model's predictive capability and ease of application, thereby advancing the field of tactile evaluation. The authors believe that this model offers a valuable reference for the design and manufacturing of custom wardrobes, with promising application prospects and practical value.

CONCLUSIONS

1. This study successfully developed an evaluation model based on a back propagation (BP) neural network for accurately predicting and evaluating the tactile experience of custom wardrobe finishes. Utilizing Matlab software, a mapping model between the "Physical Attributes Layer" and the "Tactile Sensation Layer" of custom wardrobe finishes was constructed. Demonstrated on 42 training samples and 14 validation samples, the model showed outstanding predictive consistency and accuracy, proving its significant advantages over traditional multiple linear regression analysis in predicting the quantitative values of tactile adjectives in the "Tactile Sensation Layer."
2. The research found that tactile adjectives significantly influence users' tactile satisfaction between the "Tactile Sensation Layer" and the "Comprehensive Evaluation Layer." Users in Nanjing, China, prefer finishes that are delicately textured, gentle to the touch, and common, which not only helps to alleviate stress and provide emotional value but also matches the functional needs of personal spaces like bedrooms. Furthermore, the issue of collinearity in the model was addressed through principal component analysis, constructing an effective method to predict tactile satisfaction.
3. The model equips designers with a predictive tool to ascertain quantitative values of target tactile adjectives for new finishes, based on the physical parameters of custom wardrobe design elements. This enables designers to comprehend target users' tactile perceptions of new finishes and forecast their satisfaction with the tactile experience. Consequently, this guidance informs subsequent design work, markedly reduces the design iteration cycle, and enhances design accuracy.

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