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SENSORY STYLING DESIGN OF PHYSIOTHERAPY BEDS BASED ON BP NEURAL NETWORK

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Abstract. There is a significant gap between the form of current physiotherapy beds and users' perceptual images. By employing techniques such as computer graphic design and logical operations, analyzing the mathematical relationship between user needs and design elements contributes to enhancing the scientific nature of product design and making the design process more rigorous. This paper, based on an analysis of the product image and design process, employs a comprehensive fuzzy evaluation method to identify representative perceptual vocabulary for physiotherapy beds. The KJ method and Delphi method are utilized to select necessary samples. A morphological analysis matrix is established using the morphological analysis method, and a comprehensive decision-making model for product design is constructed using a BP neural network on the MATLAB platform. Through training the BP neural network on physiotherapy bed products, it becomes possible to predict the perceptual evaluation of product design, achieving a quantification of the design. This provides valuable support for the appearance design of physiotherapy bed products and significantly enhances the efficiency of designers' work.

Key words: BP neural network; Physiotherapy bed; Perceptual image; Modelling design

1. Introduction. In recent years, physiotherapy methods have matured, leading to the active involvement in China about the exploration of physiotherapy products [1]. With increased health awareness and advances in medical technology, the demand for physiotherapy beds has gradually risen. Currently, there is a structural disparity between users' perceptual demands and designs for these physiotherapy products, evolving from rigid requirements to perceptual needs [2]. Beyond functional requirements, users also prioritize inner emotional experiences, necessitating designers to convey product characteristics through specific forms. Therefore, assessing the perceptual cognitive elements in product design holds crucial significance in shortening design cycles and reducing development costs.

As a design approach that translates users' perceptual images into design elements, Kansei Engineering aligns with the trend of constructing mathematical models for quantified research objectives [3]. In past practices, Zhao Yanan et al. constructed a Kansei image prediction model for office chairs based on a BP neural network [4]. Ding Lu et al. applied a BP neural network to optimize the overall design of a programmable paper cutter, yielding improved results in perceptual design [5]. Ma S and Yan X designed an intelligent clothing pattern design system based on BP neural network [6]. Chen DL also combined Kansei Engineering and BP neural networks in the development of a product form design system [7]. However, in the application process, subjective methods often dominate the selection of one or multiple suitable perceptual terms. The utilized BP neural network typically retains a single hidden layer even when dealing with multiple outputs, limiting selection and resulting in lower accuracy. This can lead to non-scientific neural network outputs or suboptimal weight allocation.

Thus, this paper, after obtaining raw data through multiple questionnaire surveys and conducting multivariate analysis and cluster analysis using SPSS, identifies representative perceptual vocabulary for physiotherapy bed design. The morphological analysis method is employed to deeply deconstruct the design elements of physiotherapy beds, resulting in a comprehensive perceptual image assessment matrix. For cases involving multiple outputs, a BP neural network is designed with multiple hidden layers to increase combination possi-

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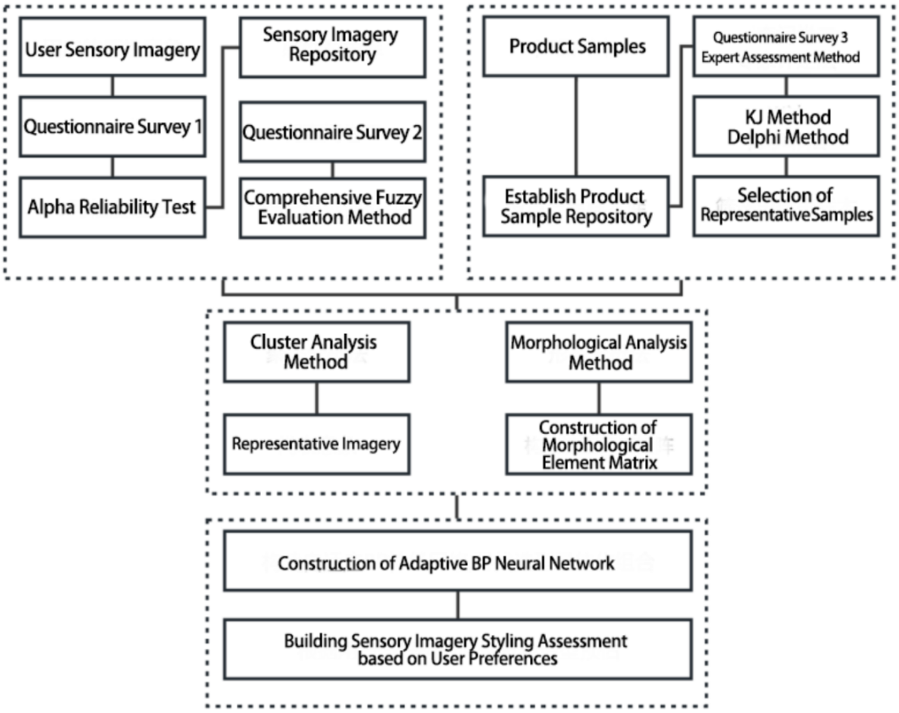

Fig. 2.1: Research Process and Methodology.

bilities, establishing a mapping relationship between the two. Simulated predictions are performed to render the previously experientially driven design process more scientifically grounded.

2. Research Process and Methodology. When considering the conceptual design output, designers need to combine user requirements, design patterns, and bidirectional inference [8]. This involves transforming users' subjective perceptions into comprehensible images, effectively integrating the visual attributes of a product with users' perceptual images. In light of the specific details of the research, this paper establishes the research framework into four main sections, as illustrated in Figure 2.1.

2.1. Collection and Selection of Perceptual Images. In this phase, a diverse range of perceptual vocabulary is gathered to express various potential perceptual images, utilizing these words to embody and elucidate the semantic aspects of the product. This enables the analysis of human perceptions to derive novel content for product development [10]. Based on the Semantic Differential (SD) method questionnaire results, this paper employs comprehensive fuzzy evaluation. As the representative samples are formed in the cognitive space dimension based on the size of the sample population and the complexity of the design form, mathematical techniques such as multivariate analysis and cluster analysis are utilized to establish representative images.

2.2. Sample Filtering and Selection. A crucial step in extracting users' perceptual images involves obtaining samples through methods like interviews or surveys. The sample repository typically encompasses physical samples and virtual samples. Physical samples refer to tangible products available on the market, while virtual samples are designs simulated by various designers. Thus, this paper collects product design samples from sources such as online marketplaces, official company websites, and journals. The representative sample library within these design samples then needs to be selected.

2.3. Construction of Product Design Elements Repository. The repository of product design elements serves as the foundation for constructing perceptual image designs. Products are defined by multiple categories, each containing diverse design elements. Additionally, functional deconstruction of products is necessary to focus on the primary functional units, reducing the influence of other factors. Therefore, in analyzing design elements, categorization is based on design characteristics and functional components.

2.4. Establishment of Product Image Design Model. The construction of image design models often relies on intelligent algorithms in computing, frequently using methods such as BP neural networks, ant colony algorithms, genetic algorithms, and support vector machines [9]. BP neural networks, a powerful algorithm, possess strong nonlinear mapping capabilities. They emulate biological neural processing systems and unique human learning and cognitive patterns [10]. Due to their effectiveness in managing and establishing complex relationships between input and output variables, they find extensive application in product design and related fields [11].

3. Handling User Perceptual Images. The perceptual images obtained from the questionnaire survey serve as raw data. Given the vagueness and complexity of perceptual images, it's necessary to perform quantitative processing on the collected perceptual images.

3.1. Categorization and Fitting of Perceptual Images. The perceptual images collected through user surveys tend to be scattered and lack concentration, making it difficult to identify representative vocabulary or determine the number of categories. Commonly, previous research has relied on subjective judgment for categorization. Therefore, this paper aims to determine the number of categories for perceptual images through distributing questionnaires and processing the data.

In the questionnaire survey, participants are asked to group semantically similar words into the same category. The number of categories ranges from 4 to 10, with varying word counts per group, ensuring that all words are used without repetition. Based on the grouping results, the frequency of pairs of perceptual image words being placed in the same category is calculated, leading to the creation of a matrix of similar frequencies.

Considering the fit analysis of perceptual image words along with the content analysis, the dimensions of the matrix are set to M*M, where M represents the number of initial perceptual images collected. The matrix is represented using $\Delta = (\mathrm{x_{ij}})\,(\mathrm{i,j} = 1, 2 \ldots 40)$, as shown in formula 3.1.

$$\Delta = \begin{pmatrix} \mathrm{X}_{1,1} & \cdots & \mathrm{X}_{1,40} \\ \vdots & \ddots & \vdots \\ \mathrm{X}_{40,1} & \cdots & \mathrm{X}_{40,40} \end{pmatrix}$$

$\mathrm{x_{ij}}$-The frequency of the i-th word and the j-th image appearing in the same category. Based on the matrix of similar frequencies, we can utilize Multidimensional Scaling (MDS) to assess the fit between words, enabling a deeper exploration of their underlying relationships and calculating their coordinates in a lower-dimensional space. MDS constructs a distance matrix $\mathrm{D_{ij}} = (\mathrm{d_{ij}})$ between objects based on the similarity matrix $\mathrm{C_{ij}} = (\mathrm{c_{ij}})$, with the transformation between data represented by formula 3.2.

$$\mathrm{d_{ij}} = \sqrt{(\mathrm{c_{ii}} + \mathrm{c_{jj}} - 2\mathrm{c_{ij}})}$$

By performing k-dimensional fitting, we can generate a grid X of size $\mathrm{n} * \mathrm{k}$, which corresponds to a complex system composed of a distance matrix in the form of $n*k$. This system contains off-diagonal elements. Through arranging these elements and understanding their relationships, effective fitting in K-dimensions can be achieved. To facilitate k-dimensional fitting, a grid X of size $\mathrm{n} * \mathrm{k}$ is constructed, with X corresponding to a distance matrix $\widehat{\mathrm{D}}_{\mathrm{ij}} = \left(\widehat{\mathrm{d}}_{\mathrm{j}}\right)$ that contains information as in equation $D_{ij} = d_{ij}$. Non-diagonal elements from $D_{ij} = d_{ij}$ are selected, sorted in ascending order, and labeled as follows:

$$S^2(\widehat{X}) = \frac{\min \sum_{ipj} \left(d^*_{ij} - \widehat{d}_{ij}\right)}{\sum_{ipj} d^2_{ij}}$$

Table 3.1: Fitting Goodness Empirical Criteria.

Stress Value	Fitting Degree	Stress Value	Fitting Degree
Stress 20%	Poor	Stress 2.5%	Very Good
Stress 10%	Satisfactory	Stress=0	Perfect Match
Stress 5%	Good		

Adjusting $\mathrm{d}_{\mathrm{ij}}^{*}$ to achieve the maximum value of $\mathrm{S}^2(\widehat{\mathrm{X}})$, at this point, $\{\mathrm{d}_{\mathrm{ij}}\}$ corresponding to the extreme minimum value of $S^2(\widehat{\mathrm{X}})$ is referred to as the least squares regression of $\{\mathrm{d}_{\mathrm{ij}}\}$. It is assumed under the premise of invariance, and there exists a $\widehat{\mathrm{X}}$ such that:

$$\mathrm{S}^2(\widehat{\mathrm{X}}) = \min_{\mathrm{X}_{\mathrm{n+k}}} \mathrm{S}(\widehat{\mathrm{X}}) = \mathrm{S}_{\mathrm{k}}$$

In this case, $\widehat{X}_0$ is referred to as the best-fitting construction point, while S_k represents the pressure index. Once the perceptual image vocabulary objects in the K-dimensional space are positioned, their original similarity can be reflected by transforming the "distance" coordinates between each word. To assess the fitting effectiveness in the K-dimensional space, the matrix is multidimensionally unfolded, and their composite degree is determined based on the empirical standard of fitting goodness. The criteria for fitting goodness are presented in Table 3.1.

3.2. Selecting Representative Perceptual Vocabulary. After obtaining the number of clusters K for the perceptual image vocabulary, further dimension reduction will be carried out using clustering methods to obtain representative perceptual image vocabulary. Common clustering methods include hierarchical clustering and K-means clustering. In this study, hierarchical clustering will be employed for clustering. By comparing the clustering results, the optimal output solution for representative perceptual image vocabulary clustering will be chosen.

Hierarchical clustering is an approach that organizes data through successive splitting and merging, resulting in a hierarchical tree-like structure. In hierarchical clustering, the Euclidean distance is commonly used as the calculation criterion, and the between-group average linkage method is employed. The distance from sample x to cluster G is defined as shown in formula 3.5.

$$D(x-G) = \frac{1}{n}\sum_{j=1}^{n} D\left(x-g_j\right)$$

n represents the number of samples in the cluster; x represents the number of cases in cluster $G; D\left(c-g_j\right)$ represents the Euclidean distance between a case and another case within cluster G. After conducting hierarchical clustering analysis using SPSS, a dendrogram representing the clustering analysis is obtained. Based on this dendrogram and the predetermined number of clusters K, representative perceptual vocabulary for the product can be identified.

4. BP Neural Network Design. BP neural networks possess the advantage of the error backpropagation algorithm, enabling effective modeling of complex nonlinear functions. This provides an efficient approach to explore the design of physiotherapy beds and its connection with other similar design requirements.

4.1. Structure of the BP Neural Network. A BP neural network consists of an input layer, hidden layers, and an output layer, with varying numbers of interconnected neurons between layers. Signals propagate forward through the input, hidden, and output layers, while errors propagate backward in the opposite direction, iteratively adjusting the weights and biases between layers. Iteration continues until the output error meets the desired precision or a preset number of iterations is reached. The topology of the BP neural network is illustrated in Figure 4.1.

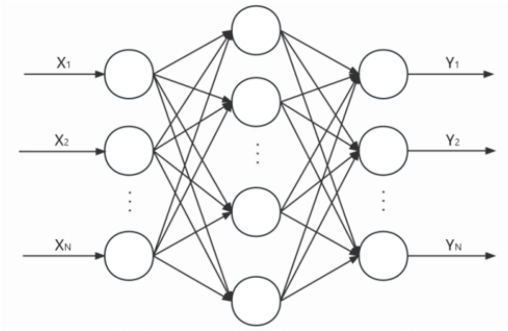

Fig. 4.1: Structure of the BP Neural Network.

4.2. Determining the Number of Hidden Layer Neurons. The number of neurons in the hidden layer plays a role in uncovering underlying patterns in the training samples and converting them into weights. The quantity of hidden layers also impacts the accuracy of the BP neural network. Too few hidden layers can compromise the approximation precision of nonlinear functions, while too many may lead to longer training times and overfitting. Determining the number of neurons in the hidden layer generally relies on empirical formulas to avoid futile attempts and unnecessary calculations. Therefore, an empirical formula is employed here using a trial-and-error method for determination. The preliminary range for estimation is shown in formula 4.1.

$$\mathrm{L} < \sqrt{\mathrm{M}+\mathrm{N}}+\mathrm{A}$$

L - Number of neurons in the hidden layer; M - Number of neurons in the input layer; N - Number of neurons in the output layer; A - Adjustment constant typically taken between 1 and 10

4.3. Selection of Activation Function. In the BP neural network, the transfer function employs a nonlinear transformation function, specifically the Sigmoid function. This function is further divided into unipolar and bipolar types. In the neural network constructed in this paper, the unipolar version will be employed, as shown in formula 4.2, with a value range of $(0,1)$.

$$\log \mathrm{si}(\mathrm{x})=\frac{1}{1+\mathrm{e}^{-\mathrm{x}}}$$

Meanwhile, the output layer will employ the purelin function, as shown in formula 4.3 .

$$y=x$$

4.4. Data Normalization. In order to facilitate rapid convergence of the network and prevent values from being too widely dispersed, which can hinder neural network learning, data normalization is necessary to scale the data to the range $[-1,1]$. This paper will use formula 4.4 as the normalization formula.

$$\mathrm{x}_{\text{nrom}} = 2 \times \frac{\mathrm{x}^{-\mathrm{x}_{\min}}}{\mathrm{x}_{\max}-\mathrm{x}}-1$$

5. Example Verification. Using fuzzy analysis and BP neural network f innovative design of physiotherapy bed forms.

5.1. Establishment and Selection of Perceptual Images. After systematic research, a total of 145 perceptual vocabulary words related to physiotherapy beds were collected through various means such as user interviews, journals, and evaluation reports. These vocabulary words encompass research outcomes from multiple fields including perceptual engineering, design studies, and product aesthetics, in order to better represent

Table 5.1: Perceptual Image Vocabulary List after Frequency Screening.

Perceptual Image Vocabulary				
Humanized	Safe	Clean	Technological	Precise
User-friendly	Sturdy	Tidy	Practical	Professional
Stable	Friendly	Reliable	Advanced	Simple
Durable	Approachable	Efficient	Harmonious	Comfortable
Modern	Smooth	Accurate	Neat	Round
Orderly	Strong	Automated	Steady	Diamantine
Steadfast	Pleasant	High-end	Gentle	Expensive
Substantial	Organized	Elegant	Soft	Delicate

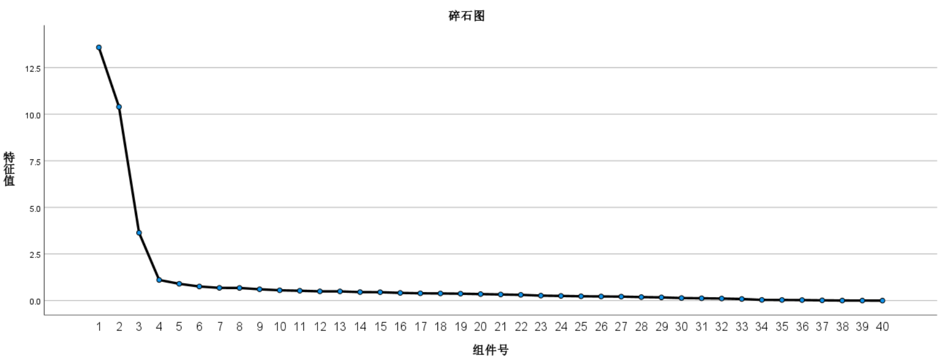

Fig. 5.1: Scree Plot of Perceptual Image.

Table 5.2: Fitting Goodness Evaluation.

Dimension	Stress ( )	Coefficient of Determination (RSQ)	Fitting Degree
4	0.049	0.973	Good
5	0.029	0.982	Good
6	0.019	0.987	Very Good
7	0.014	0.99	Very Good

user perceptual images. After thorough investigation, 152 questionnaires were distributed to engineers and designers associated with physiotherapy beds, yielding 145 valid responses. Following meticulous screening, vocabulary words with frequencies below 5% were excluded, as statistically, frequencies below 5% lack universal representativeness. This process resulted in retaining 70 more representative vocabulary words. After organizing the approximations and inconsistencies of these words, and undergoing selection by an expert group, 40 perceptual vocabulary words were obtained as the initial perceptual image library (See in table 5.1).

After involving 42 individuals with diverse backgrounds, we conducted a grouped questionnaire survey, ultimately receiving 35 completed questionnaires. Upon collecting the questionnaire data, the data was organized into a 40x40 matrix based on formula 1. The collected data was subjected to a correlation analysis of perceptual factors using SPSS. At this point, with the assistance of the scree plot in Figure 5.1, the number of factors can be inferred. When the line passes through 4, the sudden steepness becomes stable, suggesting that the optimal number of reference factors for this matrix is 4 or more groups.

Subsequently, the matrix was positioned in a K-dimensional space. After unfolding the matrix multidimensionally, coordinates for 40 vocabulary words were obtained in the K-dimensional space, as shown in Table 5.2, the fitting goodness was evaluated for dimension numbers of 4, 5, 6, and 7.

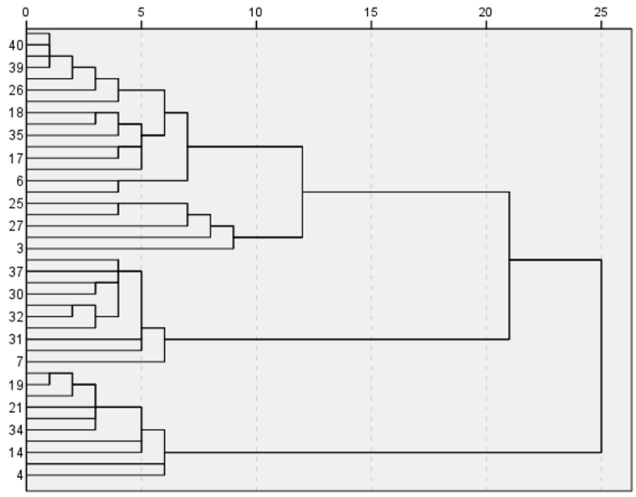

Fig. 5.2: Hierarchical Clustering Dendrogram of Perceptual Image Vocabulary.

Table 5.3: Hierarchical Clustering Grouping Results.

Group	Representative Vocabulary	Words within the Group
Group1	Safe	Technological, Precise, Sturdy, Stable, Reliable, Advanced, Durable, Efficient, Accurate, Neat, Strong, Automated, Steady, Diamantine, Expensive, Substantial, Steadfast, Modern, Professional, Organized, Delicate
Group2	Soft	Comfortable, Gentle
Group3	Friendly	Elegant, Pleasant, Round
Group4	Humanized	Harmonious, Smooth, Approachable, Orderly, High-end, Tidy, User-friendly, Clean, Simple, Practical

Considering the need for simplicity in the BP neural network's output and to avoid setting too many nodes in the output layer, it is more reasonable to set the number of clusters to 4 in the clustering analysis. Moreover, when the dimension is set to 4, with Stress $(S_k) = 0.040 < 0.05$, it indicates a good fitting. Therefore, it is judged that these 40 vocabulary words can be divided into 4 groups, obtaining the number of groups for the perceptual vocabulary in the physiotherapy bed evaluation system.

This paper will employ hierarchical clustering separately to achieve clustering. Through the comparison of clustering results, the optimal output scheme for perceptual image vocabulary selection will be chosen. In this case, 4 representative vocabulary words will be selected as the optimal output. Hierarchical clustering analysis was conducted using SPSS, resulting in a dendrogram as shown in Figure 5.2. Upon analysis, it can be determined that the representative perceptual vocabulary words are "Safe," "Humanized," "Friendly," and "Soft." Further details about the grouping results can be found in Table 5.3.

5.2. Constructing Sample Styling Feature Codes. Through online collection, a total of 68 initial samples were obtained. After undergoing the KJ method and Delphi method screening, 12 samples were selected which shared similar styling functionalities and exhibited representative qualities. Based on the morphological analysis approach, these 12 samples were deconstructed to establish a repository of styling elements. According to the functional aspects and styling characteristics of therapeutic beds, these samples were broken down into 9 distinct styling morphological elements. Each morphological element encompasses design features numbering between 3 and 6, with the aim of ensuring both comprehensiveness and specificity. Furthermore, each element was assigned a unique code, as illustrated in Table 5.4.

Table 5.4: Deconstruction Coding of Styling Design Elements.

Design Element	Type					
Base x1	1 Rectangular	2 Rod	3 Wheels	4 Trapezoidal Angle	5 Pipe-like	6
Support x2	Square	Trapezoidal	Leg	Custom Irregular Shape	Exposed Structure	One Side Suspended
Bed Surface x3	Rectangular	Two Wide, One Narrow	Circular Rectangular	One Side Narrow		
Peripheral Handles x4	None	Expandable Single-Side Handle	Expandable Dual-Side Handles			
Control Panel x5	None	Remote Control	Integrated into Bed Body	Individually Set Console		
Bed Surface Movement Structure x6	Fixed	Sectional Front-Back Extension	Sectional Vertical Movement	Sectional Vertical Tilt	Overall Vertical Tilt	
Bed Surface Material x7	Fabric	Leather	Plastic			
Color x8	Cool Tones	Warm Tones	Black and White Neutral Colors			
Fixing Device x9	None	Additional Structural Fixation	Straps Fixation			

Table 5.5: Deconstructed Design Elements

Sample	Design Element									Sensory Imagination Evaluation Average			
	x1	x2	x3	x4	x5	x6	x7	x8	x9	Safe	Humanized	Friendly	Soft
1	2	4	1	1	2	1	1	1	1	1.82	2.64	2.10	3.12
2	2	3	1	1	1	1	2	2	1	1.54	2.12	1.34	1.56
3	5	2	1	3	2	2	2	3	1	2.02	2.32	2.86	2.48
4	5	3	4	1	1	1	2	3	2	2.74	2.34	1.86	1.42
5	3	5	4	1	3	4	2	3	2	1.98	3.02	1.32	2.22
...	...	...	...	...	...	...	...	...	...	...	...	...	...
...	...	...	...	...	...	...	...	...	...	...	...	...	...
49	2	3	1	3	3	1	1	3	2	2.10	1.84	2.92	2.78
50	1	5	4	1	2	4	2	3	2	1.62	1.58	1.886	1.70

5.3. Evaluation of Sensory Imagination for Physiotherapy Beds. Based on the research questionnaire statistics and the summarized sensory evaluation average values, as well as the deconstruction of the design elements of physiotherapy beds, a sensory evaluation matrix consisting of fifty samples and ”nine sensory imageries” was established. The conformity was measured using a 1-5 Likert scale, where a score of 1 indicates non-conformity and a score of 5 indicates complete conformity. After conducting questionnaire surveys with 34 design professionals and 16 non-design professionals, the evaluations were averaged to study the preference of the survey subjects towards the samples. The partial data from the table can be found in Table 5.5.

Based on the aforementioned analysis, the BP neural network is constructed using the MATLAB 2022 software. Given the network's characteristic of multiple inputs and multiple outputs, an additional hidden

Table 5.6: Model Accuracy under Different Hidden Layers.

Hidden Layer Neurons	Mean Absolute Error (MAE)	Mean Squared Error (MSE)	Root Mean Squared Error (RMSE)	Hidden Layer Neurons	Mean Absolute Error (MAE)	Mean Squared Error (MSE)	Root Mean Squared Error (RMSE)
5	0.23097	0.10847	0.32935	10	0.16461	0.048648	0.22056
6	0.18153	0.055638	0.23588	11	0.11175	0.019345	0.13909
7	0.18106	0.045277	0.21278	12	0.31526	0.19502	0.44161
8	0.21159	0.061676	0.24835	13	0.21998	0.05842	0.2417
9	0.15716	0.04218	0.20538	14	0.2025	0.06482	0.2546

layer is introduced to determine the optimal number of neurons. Since the network entails 9 design elements, the input layer comprises 9 nodes. Correspondingly, there are 4 sensory imaginations being evaluated, leading to the output layer containing 4 nodes. Computed according to the empirical formula in formula 6 , with $M = 9$ and $N = 4$, the value of $L < 5 \sim 15$ is obtained.

For the purpose of accurate performance assessment, the MAE function is utilized. This function is less susceptible to the influence of outliers, allowing for a more precise depiction of data distribution. The specific formula for MAE is as follows:

$$\mathrm{MAE} = \frac{1}{m} \sum_{\mathrm{i}=1}^{\mathrm{m}} \left|\mathrm{y_i} - \mathrm{f}\left(\mathrm{x_i}\right)\right|$$

$\mathrm{y_i}$-denotes the actual value for the i-th sample. $\mathrm{f}(\mathrm{x_i})$-signifies the predicted value by the neural network for the i-th sample. Utilizing the MATLAB software, various parameters were trained, and the corresponding error results for each parameter were presented in Table 5.6.

From Table 5.6, it is evident that when the number of neurons in the hidden layer is 11, both the training model's Mean Squared Error (MSE) and the validation model's MSE are minimized. Therefore, for this neural network architecture, the optimal number of neurons in the hidden layer is chosen to be 11. The BP neural network structure is set as 9*11*11*4, with a learning rate of 0.1 and an expected error of 0.00001. Following the specified criteria, the optimal network is trained and stored as the final quantitative relationship model for the design. The model is established using the purelin transfer function and trained using the gradient descent method.

The correlation coefficient between the training results and the actual evaluation data is R=0.96359, as shown in Figure 5.3. This indicates a high level of prediction accuracy for the model, demonstrating a strong fitting effect on the training dataset.

Model Practical Testing. Once the neural network is established, it can serve as a reference for the design of the therapeutic bed's visual imagery, providing design directions for designers. However, it is necessary to demonstrate its functional rationality. Therefore, different design proposals will be subjected to performance testing using the established BP neural network. To perform cross-validation, five industrial designers will each provide a set of therapeutic bed design proposals. These proposals will be adjusted and modeled in the Rhinoceros software to incorporate the model's design factors, resulting in five sets of therapeutic bed designs. Material and color design will be applied, and the models will be imported into Key shot for rendering. The specific proposals can be seen in Figure 5.4.

These five proposals will undergo expert scoring to obtain actual evaluation values. Subsequently, the five samples to be verified will be encoded according to Table 5.2 and used as input to the constructed BP neural network. The obtained indicator values from the output layer will be compared with the actual evaluation values to determine the relative error in predicted evaluation values.

Based on the data presented in Table 5.7, it is evident that the results generated by the neural network closely align with the evaluations conducted by experts, with a maximum deviation of only 8.5% and a minimum deviation of just 0.8%. This finding demonstrates that the trained neural network for design imagery

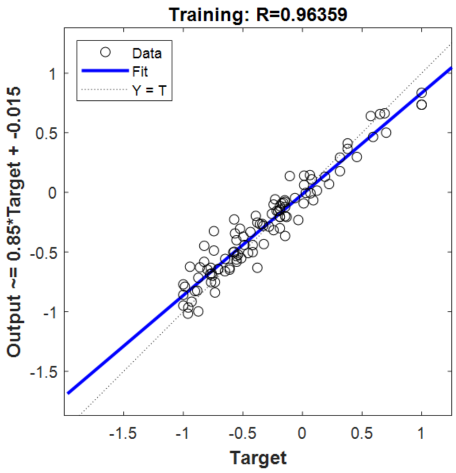

Fig. 5.3: Fitting Goodness of the Training Set.

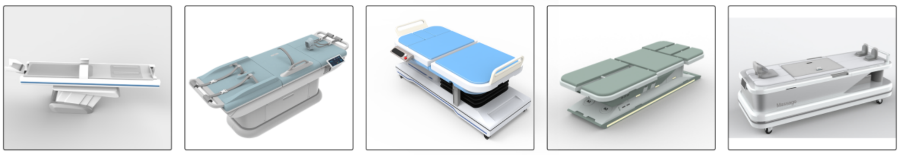

Fig. 5.4: Neural Network Training and Testing Scheme.

Table 5.7: Verification and Comparison Results.

Sensory Vocabulary	Data Error	Sample 1	Sample 2	Sample 3	Sample 4	Sample 5
	Predicted Sensory Value	2.1	3.60	1.96	1.64	1.84
Safe	Actual Sensory Mean	2.28	3.80	2.02	1.60	1.82
	Relative Error (%)	8.5%	5.6%	3.1%	2.4%	1.1%
	Predicted Sensory Value	2.1	2.84	1.82	2.19	1.66
Humanized	Actual Sensory Mean	2.06	2.62	1.80	2.10	1.62
	Relative Error (%)	1.9%	7.7%	1.1%	4.1%	2.4%
	Predicted Sensory Value	2.9	3.48	2.42	2.26	2.32
Friendly	Actual Sensory Mean	2.84	3.38	2.36	2.12	2.28
	Relative Error (%)	2.1%	2.9%	2.5%	6.2%	1.7%
	Predicted Sensory Value	3.61	2.67	2.18	2.72	2.32
Soft	Actual Sensory Mean	3.64	2.60	2.00	2.68	2.14
	Relative Error (%)	0.8%	2.6%	8.3%	1.5%	7.7%

can effectively capture the sensory characteristics of the therapeutic bed. Consequently, this network can be employed to comprehensively assess the visual design of therapeutic beds. By employing the neural network model, designers are empowered to move beyond relying solely on experience and sketches to infer the overall appearance of therapeutic beds. This design approach is notably more precise and scientifically grounded.

6. Conclusions. By applying the BP neural network model, we were able to establish a more scientifically grounded connection between the overall visual design elements of the physiotherapy bed and users' sensory imaginations. Additionally, we could enhance the precision of understanding users' emotions, enabling designers to better employ design language to convey the product's meaning. The introduction of mathematical evaluation models helps overcome the limitations of solely relying on designers' subjective experiences in the original design process. This significantly reduces design risks and facilitates more informed decisions for visual design. However, the design of a physiotherapy bed, being a versatile medical rehabilitation equipment, also involves various factors such as specific functional requirements, internal operational structures, material choices, and human-computer interaction. These factors could serve as inputs for the BP neural network or other mathematical models, establishing logical connections between them and users' sensory demands. Furthermore, different neural network architectures or training functions can be utilized to obtain diverse sensory perception evaluation averages, thus balancing the diverse needs of users. With the extensive application of machine deep learning techniques in product sensory image design, more comprehensive and powerful mathematical models will likely facilitate further development in research on design methods based on sensory ergonomics.

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