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Practice of Cognitive Function and Computational Model Fusion in Smart Product Design Optimization

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ABSTRACT

In order to improve the design of intelligent products, user cognition and perceptual engineering are integrated into intelligent product design. And through subjective survey and physiological measurements and other techniques to measure the user's emotional experience of the product, to construct the user's emotional evaluation model based on BP neural network. Multimodal interaction technology is used to optimize the product design method, and the implicit needs of users for intelligent products are obtained through the method of multimodal perception, which is matched with the product interaction, so as to propose the intelligent product design strategy based on multimodal interaction. In order to verify the effect of the strategy, physiological indicators and perceptual imagery are obtained to evaluate the products. Finally, the user satisfaction of intelligent products under this strategy is studied. The benefit ratio of the smartwatch designed based on the design strategy of this paper (0.438811) is better than other market competitors. The user satisfaction of the 10 experience dimensions of this smartwatch is distributed in the range of [80%, 93%], the dimension with the highest satisfaction is functionality, the lowest is attractiveness, and the overall satisfaction is 86.6%, and the smartwatch designed by this paper's design strategy obtains a high level of user satisfaction.

Keywords: user perception, perceptual engineering, multimodal interaction, user needs, user experience

1. Introduction

In recent years, more and more products have been transformed into intelligent forms through the implantation of artificial intelligence technology, providing convenience for our daily life with its perfect functions. Under the general trend of “Intelligence +”, product design has also gradually derived from the previous research on hardware development to the construction of software ecology, and the research on the interaction behavior between users and intelligent products has also been paid

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attention to [1-3]. From the perspective of intelligent products, the essence of interaction is the acquisition, processing and feedback of information, and the object of such information acquisition will focus on the commands issued by the user at the beginning, and the interaction mode is mainly the user's indirect or direct control of the hardware device through the manual operation of buttons, touch screen and so on [4-6]. However, with the development of new technologies such as natural language processing, computer vision, etc., the development of intelligent products has evolved from the original single dimension to the service circle, expecting to realize the user's experience satisfaction by creating a complete ecological service circle [7-9]. So the object of information acquisition also began to involve the physical environment, other products, and the information world. Products began to use voice recognition, image recognition, virtual reality and other technologies brought voice interaction, visual recognition and other new interaction methods, the user can release their hands to other means of operation, or even product active recognition, autonomous interaction [10-12]. This kind of interaction fits the human activity scenarios and opens up multiple modal channels to create an immersive experience in pursuit of a more natural and efficient interaction [13]. It can be found that from the passive interaction of a single product in the past to the active interaction of multi-dimensional products, the form of interaction between us and the product is being transformed to diversification, and the intelligent products have presented the trend of active, dynamic and scenario-based [14-16].

With the research of theory and technology under artificial intelligence, the focus of product design is also changing, from the beginning of product design to meet the basic needs of users to rise to the process of computer intelligence technology to realize the user's all-round experience from multiple perspectives. Intelligent system is conceptually defined as a system of intelligent systems with multiple types, levels, modes, features, phases and domains and other characteristics of generalized intelligence, as well as a variety of classes, scales, structures, parameters, characteristics and functions [17-19]. Defining intelligent system technically is to integrate “soft computing” and “hard computing” or to use a most basic hardware and software system to indicate the definition of intelligent system. From the perspective of intelligent product design, an intelligent system consists of users, intelligent products, tasks, and task objects. Intelligent products simplify the tasks required by the user while satisfying the user's needs [20-22].

With the rapid development of society, artificial intelligence product design has received more and more attention, and intelligent products are used in various aspects such as home, transportation, medical care, etc., and design ethics has subsequently become an issue worth focusing on in the current stage of artificial intelligence product design. Literature [23] conceptualized a set of intelligent virtual product development framework for industrial product development process, and carried out in-depth analysis and research, and examined through actual cases to confirm the feasibility of the proposed method. Literature [24] envisioned a set of new multifunctional structural conceptual network construction strategies, which can capture the precise information of intelligent product design from a large amount of unstructured and heterogeneous textual data, and provide information and data support for intelligent product design. Literature [25] designed a top-down smart product service development assistance system and tested its performance through eye-tracking experiments, and the study pointed out that the strategy effectively compensated for the lack of emotional elements in smart product design. Literature [26] integrates fuzzy kano, hierarchical analysis method (AHP), decision experiment and evaluation laboratory and quality function deployment to construct a smart product design methodology to satisfy customers' smart product demands. Literature [27] proposes a smart product design-finite element analysis process solution that can quickly adapt to design change trends and simulate to verify compliance with customer requirements. Literature [28] developed a set of intelligent product design methods based on digital twin technology, which demonstrates the product characteristics three-dimensionally and objectively, and combines the feasibility verification and illustration with real case feedback and practice. Scholarly research in the field of intelligent product design has carried out optimization and innovative research in the dimensions of rapid response to customer needs, compensation of emotional elements and improvement of the design process.

In this paper, user cognition and perceptual engineering concepts are integrated into the process of smart product design, aiming to improve the use experience of product users. The user experience is measured through physiological measurement technology and emotional evaluation model. Then, through the method of multimodal perception to explore the intrinsic needs of users, we propose the optimization strategy of intelligent products under multimodal interaction. In order to verify the effectiveness of the smart product design strategy based on multimodal interaction, the smartwatch designed by this strategy is used as an example to study in depth the physiological indicators and perceptual imagery evaluation of the product and the user's experience satisfaction with the product.

2. User Awareness and Product Design

2.1. User perception and perceptual engineering

2.1.1. User perception. User cognition belongs to the category of cognitive psychology, which studies the higher mental processes of human beings, mainly cognitive processes such as attention, perception, representation, memory, thinking and speech. Cognitive processes from an information processing point of view is the mainstream of modern cognitive psychology, which views human beings as an information processing system, and believes that cognition is information processing, including the whole process of encoding, storing and extracting sensory input.

Cognitive psychologists focus on the intrinsic and extrinsic drivers of user behavior, and are mainly concerned with the psychological processes that produce changes in human beings between information input and output. It has since become common in the design field as one of the most important methods for analyzing user psychology. However, scholars recognize that people cannot directly observe the subtle process of internal psychological action, but can only infer it by observing the input-output of users in specific scenarios for particular tasks. Therefore, cognitive psychologists adopt the method of predicting the real phenomena to further obtain the psychological processes that cannot be directly observed, and later this method is also used in the field of design to study user behavior, language and other related details.

2.1.2. Perceptual engineering. The theory of “perceptual engineering”, abbreviated as KE, emerged in the 1980s [29]. As a method and theory of product development, the study of perceptual engineering takes the consumer's impression, feeling, or need for a product as a design guide, and translates this description of mental imagery into design elements. Its purpose is to break away from the previous design concept that focuses more on the function and form of the product, and seeks to increase the designer's attention to the user's or consumer's intended feelings and needs in the process of designing and developing products. The model of the concept of perceptual engineering is shown in Figure 1.

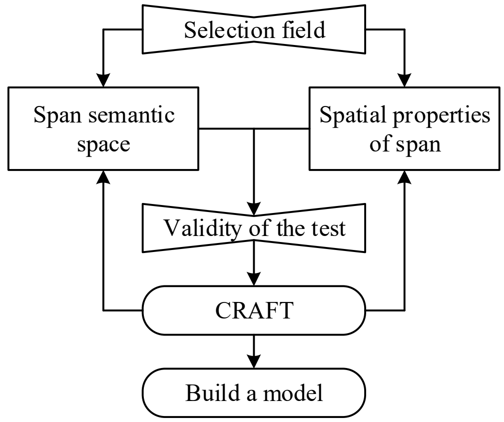

Fig. 1. Model of the concept of perceptual engineering

2.2. Emotional Measurement of User Experience

Current research mainly focuses on the combination of subjective and objective measurement methods, subjective measurement methods can directly reflect the emotional feelings of people, while physiological measurement means more objective and real, so the use of a combination of subjective and objective methods can more accurately obtain the user's true emotions.

At present, the main method of investigating the user's emotion towards the color of the product is the semantic difference questionnaire method, which is more convenient, fast and cost-saving. However, due to the differences in individual cognition, the semantic difference questionnaire does not truly reflect the user's perceptual process, and may bring some bias. With the advancement of physiological measurement technology, eye tracking and event-related potential technology in multimodal measurement means have gradually brought new ideas for measuring users' emotional experience. Physiological data comes from the human body and accompanies the whole process of the user's emotional changes, and can be obtained continuously within a certain period of time, so it can objectively reflect the user's real emotions and changes in the state.

1) Eye tracking technology. The purpose of eye-tracking technology is to obtain the results of the user's eye movements and the direction of gaze when viewing image tasks such as pictures, text or animation [30]. Eye-tracking techniques generally utilize eye-tracking instruments and accompanying software to obtain eye-movement metrics as well as cognitive processing of the user during visual tasks. The working principle of the eye-tracking instrument is to determine the pupil position and calculate the relative coordinates through image processing technology, and then use some algorithms in machine learning to further obtain the user's scanning path, pupil diameter, gaze point, and scanning point, etc., that is, to monitor the whole process of the user's "scanning-gazing-gazing", so as to understand the user's visual process of what and how to look. That is, by monitoring the whole process of "scanning-gazing-gazing", we can understand what the user is looking at, how to look at it, when to look at it and why to look at it.

2) Event-related potential technology. In the field of neuroscience, experts generally utilize electroencephalography (EEG) technology to measure the activity of the human cerebral cortex. Event-related potential (ERP) is a kind of change in brain potential caused under a particular stimulus condition, and its working principle is to superimpose the changes in brain potential caused by the same kind of stimulus many times for averaging, because the changes in spontaneous EEG are random, and the positive and negative counterbalance at the same time of superimposing and averaging with each other, and the waveform of the ERP has the characteristics of latency and waveform stabilization, the number of times of superposition will not result in the amplitude of the wave increasing, and the ERP can be easily extracted. Thus, it can be easily extracted.

ERP components can be analyzed in terms of direction, wave amplitude, time and scalp distribution. Direction is used to localize the polarity of potentials, and positive waves are defined as positive (P) waves and negative waves are defined as negative (N) waves, and the axes are currently in the form of "up-negative-down-positive". The magnitude of the waveform represents the amount of brain energy expended during brain activity. The latency is the time in milliseconds (ms) that the waveform appears, reflecting the time and speed of processing of neural activity. Brain signals at different scalp distributions represent different perceptual behaviors, and the cerebral cortex is divided into frontal, temporal, parietal, and occipital lobes depending on the user's perception of the stimulus.

3) Eye tracking technology. Eye-tracking technology is believed to be derived from the "brain-eye" hypothesis, that is, people see the information transmitted to the brain, the brain controls the eye movements, so the detection of eye movements can be inferred to some extent by the brain's activity information. Using the eye movement combined with EEG emotion cognition acquisition technology can deeply study the unconscious behavior of users and more accurately explain the processing mechanism of users' emotion cognition.

3. Intelligent product design based on multimodal interaction

3.1. Multimodal Interaction

In multimodal interaction, the user and the external things transfer information through multiple modalities so as to fulfill the whole communication needs [31]. In this process, modality does not only refer to some kind of senses, perception, but also need to utilize the senses to become a resource for generating meaning and information interaction. From the result, transferring information is its most central purpose, and multimodality provides multiple channels for information transfer, which complement/replace each other to enhance the efficiency and accuracy of information transfer and achieve a low-load interaction experience.

3.2. User demand acquisition based on multimodal sensing

In this paper, we propose the Metaphorical Elicitation Technique (MB-MET) based on multimodal perception to deeply excavate users' invisible needs and integrate them into the design of smart products.

3.2.1. MB-MET methodology user requirements acquisition process. MB-MET method is a logical psychological metaphor elicitation analysis process, which can tap the deepest human needs, the specific process is as follows:

1) Selection of target users. According to the product design positioning, the selection conditions of target users, including age, occupation, income and other personal information. Select the users who meet the requirements through the screening conditions, and the collection of N user is recorded as $B = \{b_1, b_2, b_3, \ldots b_n\}$. Train the users so that they can have an understanding of the product theme, and then tell them to collect the material related to the product such as pictures, material samples, odor samples, sounds, videos, and so on according to their own preferences through about one week's time. The set consisting of the material collected by N users is denoted as $S = \{S_1, S_2, S_3, \ldots S_n\}$, where the set of material collected by the i th subject is denoted as S_i:

$$S_i = (t_w; c_x; q_y; s_z; j_a; g_b) \tag{1}$$

$$w = 1, \ldots, W; x = 1, \ldots, X; v = 1, \ldots, V; z = 1, \ldots, Z; a = 1, \ldots, A; b = 1, \ldots, B \tag{2}$$

where t_w represents W images, c_x represents X material samples, q_y represents V odor samples, and s_z represents Z audio files. j_a represents A interaction videos, g_b represents

B functional videos.

2) Elicit the metaphorical semantics of the user's needs. Face-to-face in-depth interviews were used. First, the target users were allowed to freely explain their reasons for choosing the relevant material, and in-depth interviews are an unstructured form of interviews that can capture the users' potential desires and ideas. Then, the main test obtained key metaphors from the users through the interviews and kept asking questions to explore the deeper meanings of these metaphors. Again, with the initial metaphors captured, the subject confirms the semantics of the user's metaphors through the "reflexive interviewing technique" (summarization and restatement). Further, the principal subject used the "pulling technique" to obtain other results associated with the user metaphors until most of the deeper metaphors of a single user were defined and confirmed. All users proceeded in turn until the metaphors of all material from all users were mined and expressed in words. Let the metaphor obtained by subject i for the material be: $y_i = (y_i(t_w); y_i(c_x); y_i(q_y); y_i(s_z); y_i(j_a); y_i(g_b))$, then the set of metaphor semantics for all subjects is: $Y = \{y_1; y_i; \ldots y_n\}$.

3) User requirement metaphor analysis and processing. Analyze and process the original information of user's metaphors, merge the repeated metaphors, and standardize the original metaphor information into adjectives. The standardized user requirement metaphor semantic set is obtained as $B = \{B(y_1); B(y_i); \ldots; B(y_n)\}$, where $B(y_i) = (By_i(t_w); By_i(c_x); By_i(q_y); By_i(s_z); By_i(j_a); By_i(g_b))$.

4) Obtain the user requirement metaphor semantic set. After standardizing the user demand metaphors, the demand metaphor semantics are clustered by semantic similarity algorithm to get the user demand semantic set.

3.2.2. User Requirements Semantic Similarity Clustering:

1) User Requirements Semantic Similarity Algorithm. Due to the differences in the expression habits of different users, they may have different semantics for the same or similar implicit needs. In order to grasp the overall trend of the implicit needs of the target user group, it is necessary to analyze the correlation between the metaphorical semantics of different user needs. The semantic similarity calculation can be used to accurately cluster the semantics of users' needs. An important parameter for calculating semantic similarity is word distance, which represents the degree of similarity between a pair of words, the closer the word distance, the higher the similarity between the words. The farther the word distance, the lower the similarity between words. The word semantic similarity formula is:

$$Sim(c_1, c_2) = \frac{\alpha}{Dis(c_1, c_2) + \alpha} \tag{3}$$

where, c_1, c_2 - represents semantic word pairs. $Sim(c_1, c_2)$ - semantic similarity. $Dis(c_1, c_2)$ - semantic distance. α - the value of the semantic distance when the similarity is 0.5.

This paper adopts a semantic similarity calculation method based on "Synonyms", a Chinese synonym database based on the Wikipedia Chinese corpus. In "Synonyms", words are described by multiple "Yiyuan", which is the most basic unit of meaning in "Synonyms". By calculating the semantic similarity of "Yiyuan", the semantic similarity between the two words can be obtained. Suppose word c_1 consists of i "meaning primaries", then $c_1 = (p_1^1, p_2^1, \ldots, p_i^1)$, $i = 1, 2, \ldots, I$. Suppose the word c_2 consists of j "meaning primaries", then $c_2 = (p_1^2, p_2^2, \ldots, p_j^2)$, $j = 1, 2, \ldots, J$. In order to calculate the semantic similarity between words c_1 and c_2, the similarity between the "semantic origins" is first calculated. The semantic similarity between "Yiyuan" p_1 and p_2 is calculated as follows:

$$Sim(p_1, p_2) = \frac{\alpha}{d + \alpha} \tag{4}$$

Wherein, d - the path length of "Yiyuan" p_1 and p_2 in the "Yiyuan" hierarchy.

According to the definition of semantic similarity of the words "Synonyms", the semantic similarity of words c_1 and c_2 is the maximum similarity of each "semantic primature", that is:

$$\begin{cases} Sim(c_1, c_2) = \max sim(p_i^1, p_j^2) \\ i = 1, 2, \ldots, I;\ j = 1, 2, \ldots, J \end{cases} \tag{5}$$

The clustering of user requirement semantics first aggregates individual requirement semantics into semantic collection subclasses, further clusters semantic collection subclasses into semantic collection subclasses, and finally forms one or several requirement semantic clustering collections. Thus, in addition to calculating the similarity between individual requirement semantics, it is also necessary to calculate the semantic similarity between different requirement semantic collections. Let the set consisting of i requirement semantics be $Cy_1 = (c_1^1, c_2^1, \ldots c_i^1), i = 1, 2, \ldots, I$. The set consisting of j requirement semantics be $Cy_2 = (c_1^2, c_2^2, \ldots c_j^2), j = 1, 2, \ldots, J$. The similarity of semantic sets Cy_1 and Cy_2 is defined as the value that minimizes the similarity of requirement semantic word pairs between requirement semantic sets, i.e.:

$$\begin{cases} Sim(Cy_1, Cy_2) = \min Sim(C_i^1, C_j^2) \\ i = 1, 2, \ldots, I;\ j = 1, 2, \ldots, J \end{cases} \tag{6}$$

2) User demand semantic clustering model. Based on the demand semantics obtained by MB-MET metaphor elicitation technique, clustering is performed according to the dimensions of pictures, material samples, odor samples, audio, interaction videos, function videos, etc. related to the demand metaphors, and the demand semantics under each cluster are aggregated according to the semantic similarity from the bottom up to get a set number of demand semantics sets finally.

(1) Obtain demand metaphor semantic clusters. The standardized user requirement metaphor semantics are divided into clusters according to the six dimensions of the requirement metaphors: pictures, material samples, odor samples, audio, interactive video, functional video, etc., and the set of user requirement metaphor semantics in different dimensions is obtained, and the collection of picture metaphor semantics is as follows: $By_i(t_w), i = 1, 2, \ldots, n$. The collection of material metaphor semantics is as follows: $By_1(c_x), i = 1, 2, \ldots, n$. The collection of odor source metaphor semantics is as follows: $By_i(q_y), i = 1, 2, \ldots, n$. The collection of audio metaphor semantics is as follows: $By_i(s_z), i = 1, 2, \ldots, n$. The collection of interaction video metaphor semantics is as follows: $By_i(j_a), i = 1, 2, \ldots, n$. The functional video metaphor semantic set is: $By_i(g_b), i = 1, 2, \ldots, n$.

(2) For each dimension, construct the symmetric matrix of requirement metaphor semantic similarity. The original vector space of user's implicit demand metaphor semantics under each dimension is $By = (c_1, c_2, \ldots c_s)$, and the semantic similarity between two demand metaphor semantics is obtained through the Synonyms corpus to construct the symmetric matrix of demand metaphor semantics similarity:

$$T = \begin{bmatrix} 1.0 & Sim(c_1, c_2) & \ldots & Sim(c_1, c_s) \\ Sim(c_2, c_1) & 1.0 & \ldots & Sim(c_2, c_s) \\ \vdots & \vdots & 1.0 & \vdots \\ Sim(c_s, c_1) & Sim(c_s, c_2) & \ldots & 1.0 \end{bmatrix} \tag{7}$$

where, s - total number of demand metaphor semantics. $Sim(c_i, c_j) = Sim(c_j, c_i)$, $i = 1, 2, \ldots, s$, $j = 1, 2, \ldots, s$.

(3) Construct the set of primitive demand metaphor semantics topics. First assume that each demand metaphor semantics c_i in the original vector space By is a demand metaphor topic class $fc_i = \{c_i\}$, and construct the original demand metaphor semantics topic set as:

$$FBy = \{fc_1, fc_2, ..., fc_s\} \tag{8}$$

(4) Calculate the similarity between each demand metaphor semantic topic class. Bring the corresponding requirement metaphor semantic similarity in the requirement metaphor semantic similarity symmetry matrix T into Equation (6) for calculation.

(5) Generate new classes of demand metaphor semantic topics. Aggregate the classes with the largest demand metaphor semantic similarity to get the new topic classes as:

$$fc_{s+1} = fc_i \cup fc_j \tag{9}$$

where $fc_i \cup fc_j = \arg\max\left\{Sim(fc_i, fc_j)\right\}, i = 1, 2, \ldots, s, j = 1, 2, \ldots, s$.

(6) Delete fc_i and fc_j to get a new set.

(7) Repeat steps 4, 5 and 6 until the set number of clusters is reached and finished.

(8) Divide into different sets of requirement metaphor semantic subclasses $FBy^{'}$, and select the most important ones as the final set of key requirement metaphor semantic topics $FBy^{'}$:

$$FBy^{'} = \{fc_1^{'}, fc_2^{'}, ..., fc_s^{'}\} \tag{10}$$

$$FBy^{"} = \{fc_1^{"}, fc_2^{"}, ..., fc_s^{"}\} \tag{11}$$

where, $FBy^{'}$ is the set of subclasses after the user requirement metaphor semantic collection, $s^{'}$ is the number of subclasses, $s^{'} < s^{'}$. $FBy^{'}$ is the set of user requirement metaphor semantic subclasses of the final aggregation, $s^{"}$ is the number of subclasses of the final aggregation, $s^{"} < s^{'}$, and $3 \le s^{'} \le 10$.

Meanwhile, in order for the final aggregated user requirement metaphor semantic subclasses to represent the user's implicit requirements, it is necessary to ensure that the subclass collection semantic word frequency accumulates to a certain proportion, i.e:

$$\left(\sum_{i=1}^{k} \underset{\forall c_i \in By}{f}(c_i)\right) \Bigg/ \left(\sum_{j=1}^{k} \underset{\forall c_j \in By}{f}(c_j)\right) \ge 1 - \alpha \tag{12}$$

where, $By^{"} = \bigcup_{i=1}^{s^{-}} fc_i^{"} = \{c_1^{"}, c_2^{"}, ..., c_k^{"}\}$ k^{*} - the total number of requirement metaphor semantics contained in the final aggregated subclasses, $k^{"} < k^{'}$. $f(c_i)$ and $f(c_j)$ - the word frequencies of c_i, c_j in the original set of metaphoric requirement semantic topics By. α - Metaphorical requirement semantic topic coverage factor, $0 \le \alpha \le 0.15$.

3.3. Intelligent Product Design Strategies under Multimodal Interaction

3.3.1. Matching User Information Characteristics and Product Interaction Forms. In the pre-product design stage, the research and multimodal perception model are improved to obtain product characteristics and user demand information. And then summarize the user's modal characteristics through the analysis of user's multimodal information characteristics. In the process of human-computer interaction, user information characteristics include two aspects: 1. Mental aspect: attention occupation under cognitive load; 2. Physical aspect: actual modal channel occupation. First of all, the measurement of four factors, namely, effort, highlighting, expectation and value, in the mental aspect can lead to the situation of user's attention in the interaction process. In the product design stage, three main aspects are considered: functional module, appearance display and interaction form. The design of functional module and appearance display is more affected by users' own needs and product development, and the research on the factors of prominence, expectation and value under the related SEEV attention theory model can be corresponded to provide relevant data.The four factors of the SEEV model are concerned with the cognitive situation of user's attention, which is more related to the visual modality, and it can also be initially explored to find out the visual occupancy of the user's modal behaviors. The four factors of SEEV model focus on the user's attention cognition, which are more related to visual modality, and can initially explore the visual occupancy of the user's modal behavior, and carry on the quantitative analysis of other aspects of the modality.

In the design of interaction forms, it is necessary to consider based on user behavioral characteristics. Therefore, in the user multimodal information characteristic structure model around the degree of effort factors and highlighting factors, to further explore the user's characteristics in the physical aspects, through the VACP theoretical model analysis, to continue to quantify the user's actual operation of the mental burden (cognitive) and the physical operation burden situation (visual, auditory, movement), refine the user in the operation of the burden of the situation of the larger specifically embodied in which modal channel. Based on the principle of multimodal interaction balance, we adopt channel compensation and channel enhancement theory to reasonably allocate information channel resources to help users better perceive and use the product and reduce their operational burden. This corresponds to the interaction form and appearance design of the product. Through the allocation of user channel modes, we decide the appropriate functional interaction mode and the required carrier for information display of the product.

3.3.2. Intelligent Product Design Strategies from the Perspective of Multimodal Interaction. From the perspective of the three main phases of the overall design, the preliminary research phase mainly focuses on the users themselves, exploring the needs of the users in the scenarios and the pain points of using the product, and exploring the subjective behavioral motives and ideas of the users from a macro level. Using this as a benchmark, the design stage considers the setting of functions, appearance and interaction forms.

Under the perspective of multimodal interaction, the interaction between users and products changes from the original single mode to multiple modes, with the goal of providing users with a better experience and efficient information perception. Therefore, under this goal and the status quo of multi-modal interaction, the matching between the user's own attention resources, modal occupancy and the use of the product and the information conveyance is the key element in the whole perspective. Based on the proposed research of user multimodal information model and reintegration of the existing design process, the proposed intelligent product design strategy under the perspective of multimodal interaction is shown in Figure 2.

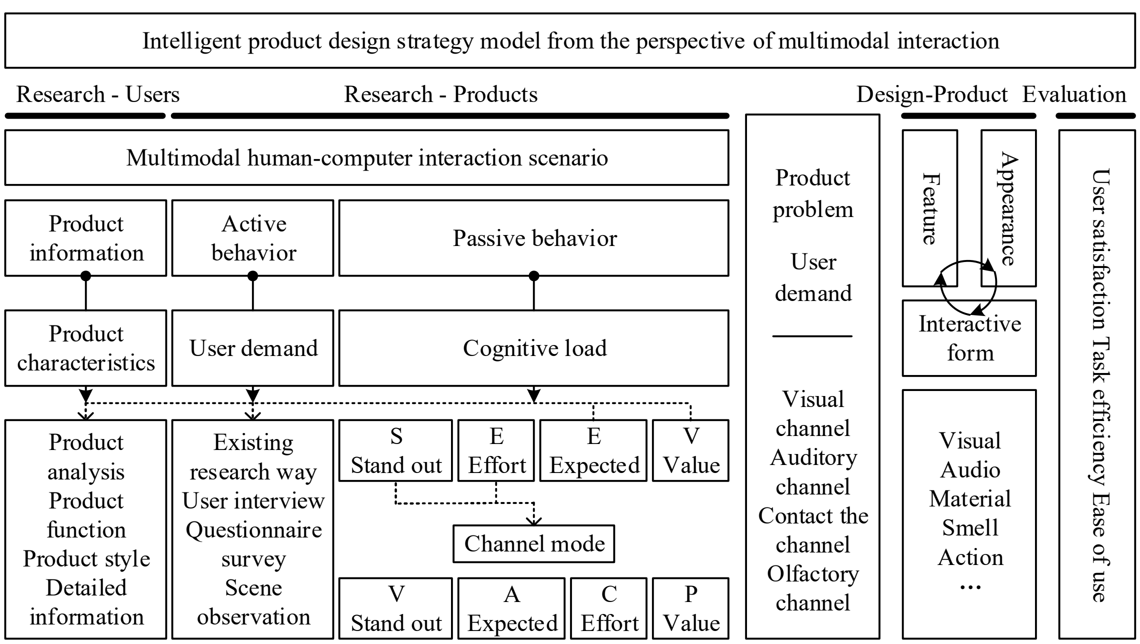

Fig. 2. Design strategy model of intelligent product under multi-modal interaction perspective

In the intelligent product design strategy under the perspective of multimodal interaction, the research stage mainly focuses on the two aspects of the product and the user in depth, using the existing research methods to obtain product information and user active behavioral information, to determine the user's needs under the scene. On the basis of this information, the user's own modal characteristics are investigated, the SEEV model is used to preliminarily explore the user's mental cognition, and the VACP model is used to analyze and refine the load of the channel module under the mental cognition. By summarizing the multimodal information characteristics of the user's mental burden and the channel physical burden, and combining the user's needs and product characteristics under the mission scenario, we can more comprehensively and accurately propose the design direction under the research stage. In the design phase, the product problems and user requirements summarized in the research mainly focus on the design of product functions and appearance, while the modal characteristics directly correspond to the selection of product interaction forms and carrying modes, and even the design of information content display.

In the whole design strategy model, the multimodal interaction perspective is introduced, which mainly emphasizes the important role of the individual's perceptual channels in the use and cognitive activities, and in the process of use, the individual's perceptual channel preferences and characteristics determine the different cognitive contents and cognitive mode differences. Under the perspective of multimodal interaction, thinking about users' sensory development and experience from the perspective of perceptual channels not only helps designers to consider how to give full play to the subjectivity of users and improve their experience according to their physiological characteristics, cognitive characteristics and cognitive modes, but also helps to think about how to design the product from the opposite perspective so as to adapt to the users' own characteristics of perceptual development and cognitive characteristics.

4. User experience analysis of smart products

4.1. Product evaluation based on physiological indicators and perceptual imagery

Take the smart watch in smart products as an example, through this paper smart product design strategy to design a smart watch (No. A), and at the same time select the other five smart watches on the market (No. B ~ F) for control, build product experience experiment the smart watch for product evaluation based on physiological activation indicators and perceptual imagery. The total number of experimental subjects is 10, and the gender ratio is male:female=1:1.

4.1.1. Physiological indicators. Six models of smartwatches were shown to the subjects, and physiological indicators such as EEG signals, ECG signals, and dermatoglyphic signals were collected from the subjects during the viewing and experiencing of the products. The physiological indicators of the subjects were noise-canceled, and the α/β amplitude ratio of the left brain region (four brain regions) was extracted from the noise-canceled EEG signals, and the values of the α/β amplitude ratios of each subject for each model of the watches are shown in Fig. 3. The mean value of LF/HF of ECG signals of each subject of each watch model is shown in Fig. 4, and the mean value of SC of the dermatoglyphic signals is shown in Fig. 5. Based on the EEG, ECG and electrodermal characteristics extracted in Figure 3~5, the physiological signal data under each style were used to identify the potency and arousal value, and the product with the highest median value - A and the product with the lowest value - F were obtained by superimposing the average of 6 smart watches, which were used as the emotional benchmark for subsequent classification.

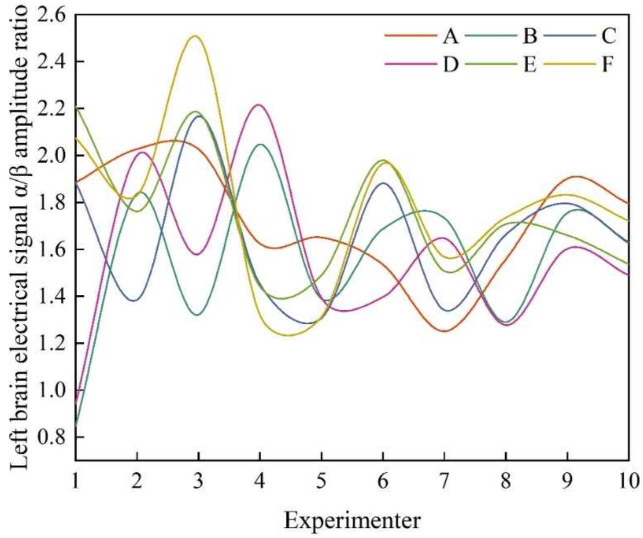

Fig. 3. The characteristics of the left brain region of the four brain regions

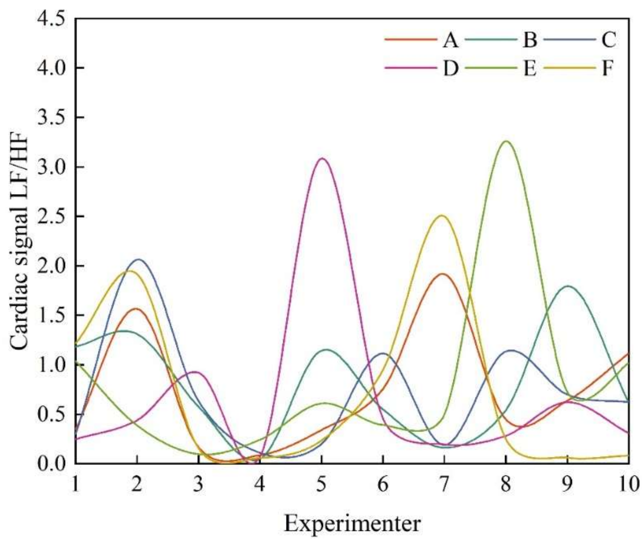

Fig. 4. The characteristics of the cardiac signal

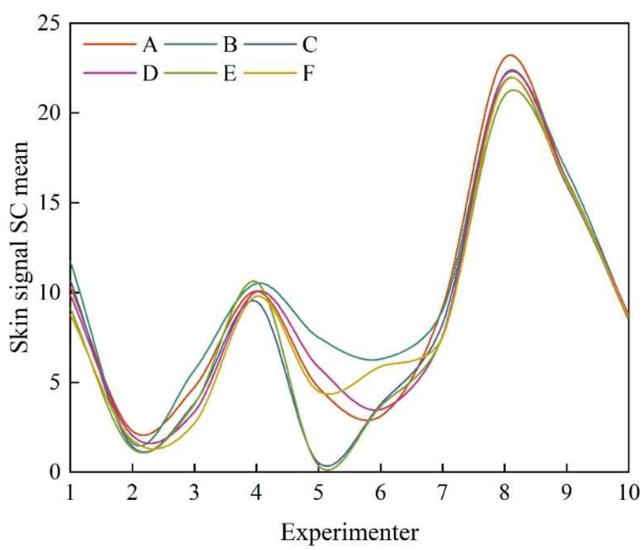

Fig. 5. The characteristics of the skin signal

4.1.2. Perceptual Imagery. Collect the imagery vocabulary about watches, after discussing and analyzing with product designers, the imagery vocabulary is determined to be delicate, fashionable, simple, functional, convenient, elegant, classic, gorgeous and intelligent. Combined with the target set of imagery to create a relevance questionnaire, the research on six smart watches, the number of researchers totaled 50 people, the gender ratio is 1:1. take exquisite as an example, the interval level of 5, the score of 1, 2, 3, 4, 5, respectively, represent very inconsistent (1), inconsistent (2), neutral (3), more consistent (4), very consistent (5). By choosing different levels to express the intensity of response and perceptual perception of the subjects between the sample and the intended word.

To test the validity of the questionnaire, SPSS software was applied to test the stability and consistency of the results of the 45 questionnaires obtained from the survey. The questionnaire Cronbach's α coefficient value is 0.957, which gives the questionnaire a very good reliability for the next step. The descriptive statistics of the correlation values for each imagery word are shown in Table 1. Mean values greater than 3 indicate that users recognize that the imagery word fits the description better, so the imagery words with mean values greater than 3 are retained and those with mean values less than 3 are discarded.

The results of the KMO test show that the value of KMO is 0.856 (KMO>0.6), indicating that there is a correlation between the variables. Using principal component analysis, a small number of imagery words that can represent the vast majority of perceptual information were extracted from the retained imagery words. The total product variance interpretation table is shown in Table 2, from which it can be seen that the use of the first four imagery words can well replace the original six imagery words.

Table 1. Descriptive statistics of imagery words

Variable name	Sample number	Maximum	Minimum	Mean	SD
Exquisite	45	5	1	2.96	1.051
Fashionable	45	5	1	2.86	1.373
Simple	45	5	1	3.92	1.538
Functional	45	5	1	4.29	1.189
Convenient	45	5	1	3.18	1.123
Elegant	45	5	1	4.13	1.541
Classic	45	5	1	3.02	1.176
Ornate	45	5	1	4.14	1.554
Intelligent	45	5	1	3.01	1.137

Table 2. Product total variance interpretation table

Ingredient	Eigenvalue	Variance interpretation rate (%)	Cumulative variance interpretation rate (%)
Functional	4.484	64.057	64.057
Ornate	0.929	13.271	77.328
Elegant	0.548	7.829	85.157
Simple	0.415	5.929	91.086
Convenient	0.268	3.829	94.915
Classic	0.202	2.885	97.800
Intelligent	0.154	2.200	100.00

A questionnaire was created based on the final imagery vocabulary, and six designs were investigated, with a total of 20 people and a gender ratio of 1:1. The evaluation method was based on a 7-point psychological scale: very unlike (1), relatively unlike (2), somewhat unlike (3), average (4), somewhat unlike (5), relatively unlike (6), and very unlike (7). In the case of “exquisite”, for example, a score of 7 means that the watch is the most relevant to the imagery, and a score of 1 means that the watch is the least relevant to the imagery. Based on the collected imagery values, the benefit ratio of each user for each watch is calculated, and the benefit ratio Q_i is used as the comprehensive evaluation value; the smaller the value of Q_i, the deepest imagery the product gives to the user. The benefit ratio Q_i is superimposed and averaged to obtain the benefit ratio of each watch, and the results are shown in Table 3. From Table 3, it can be seen that the smartwatch A designed by the design strategy of this paper achieves the best benefit ratio (0.438811) in comparison with other competitors on the market, and users have the most profound imagery of it.

Table 3. Interest ratio of all products

Product	Interest ratio Q_i
A	0.438811
B	0.597521
C	0.591668
D	0.488203
E	0.622256
F	0.496486

4.2. User experience satisfaction

In order to deeply investigate the effect of this paper's intelligent product design strategy based on multimodal interaction, the smartwatch A designed in the previous paper was put into trial, and the trial participants' feelings of using the smartwatch for a period of time (a period of two months) and their satisfaction with the product were collected. One hundred trial participants were randomly selected to participate in the experiment, with an age distribution of 26-40 years old, a mean age of 27.4 years old, and a standard deviation of 3.56. 54 of them were male and 46 were female. After filling out the experimental informed consent form, the staff introduced the experimental procedure to the trial participants. After preparation the trialists need to follow the experimental steps to complete the experimental tasks and fill in the smartwatch emotional experience evaluation scale and send it to the author.

The user experience of smartwatch A is examined in 10 dimensions: comfort, usability, functionality, pleasure, attractiveness, reliability, convenience, intelligence, cost-effectiveness, and range performance.

1) Reliability Analysis. Firstly, the questionnaire data of 100 trial participants were analyzed for reliability, and the results of the reliability analysis are shown in Table 4. By analyzing the reliability of the smartwatch emotional experience evaluation scale through SPSS, it can be obtained that the overall reliability (Cronbach's α coefficient) of the smartwatch emotional experience evaluation scale based on comfort, usability, functionality, pleasantness, attractiveness, reliability, convenience, intelligence, cost-effectiveness, and endurance performance is 0.905, which indicates that the reliability is excellent.

Table 4. Reliability analysis of emotional experience of smart watch A

Dimension	Calibration item total correlation	Deleted α coefficient	Cronbach's α
Comfort	0.51	0.67	0.905
Availability	0.68	0.76	
Functionality	0.62	0.75	
Pleasure	0.68	0.63	
Attraction	0.64	0.7	
Reliability	0.63	0.76	
Convenience	0.61	0.78	
Intelligence	0.52	0.71	
Performance and price ratio	0.48	0.64	
Battery endurance	0.51	0.66	

2) Satisfaction analysis. Statistics of smartwatch emotional experience evaluation data of the trial participants were obtained after triangular fuzzy hierarchical analysis to obtain the weights of each index. Further calculate the emotional experience satisfaction and overall satisfaction. After calculation, the satisfaction results of the emotional experience of smartwatch A designed according

to the multimodal interaction-based smart product design strategy of this paper in each dimension are shown in Table 5, and the overall emotional experience satisfaction is 86.6%. It can be seen that the intelligent product design strategy based on multimodal interaction proposed in this paper is effective for the application of ideas to meet the user's needs for intelligent products and enhance the user's experience, and the overall user satisfaction is high.

Table 5. Smart watch A emotional experience satisfaction results

Index weight	Dimension	Smart watch A emotional experience satisfaction					
		Terrible	Bad	Normal	Good	Excellent	Satisfaction
0.15	Comfort	0	0	11	37	52	89%
0.09	Availability	0	0	16	29	55	84%
0.14	Functionality	0	0	7	35	58	93%
0.11	Pleasure	0	0	8	40	52	92%
0.07	Attraction	0	0	20	36	44	80%
0.11	Reliability	0	0	16	33	51	84%
0.10	Convenience	0	0	9	25	66	91%
0.11	Intelligence	0	0	13	34	53	87%
0.06	Performance and price ratio	0	0	19	30	51	81%
0.06	Battery endurance	0	0	15	26	59	85%
Overall satisfaction		86.6%					

5. Conclusion

The article gives full consideration to the user cognition of product design, combines it with perceptual engineering, incorporates it into intelligent product design, and constructs the user emotion evaluation model. Multimodal interaction is introduced into smart product design to obtain user needs, so as to better carry out product design.

The benefit ratios of smartwatch A and other watches (B~F) designed using this paper's multimodal interaction-based smart product design strategy are 0.438811, 0.597521, 0.591668, 0.488203, 0.622256, 0.496486, and the user's evaluation of the six smart products is in the order of A>D>F>C>B>E, with smartwatch A obtaining the optimum benefit ratio and smartwatch A obtaining the optimum benefit ratio. Smartwatch A gets the optimal benefit ratio. Users' satisfaction with the 10 dimensions of the use experience of smartwatch A is not less than 80%, the dimension with the highest satisfaction is functionality (93%), and the lowest is attractiveness (80%), and the overall satisfaction with the smart product is 86.6%, which indicates that users are more satisfied with the smartwatch designed based on the product design strategy of this paper.

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