Research on Big Data and Artificial Intelligence Empowering Emotional Design of Industrial Product

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Abstract: Driven by consumption upgrading and tech innovation, industrial product design shifts from "function satisfaction" to "emotional resonance". Emotional design, key to improving user experience and competitiveness, faces bottlenecks (hard-to-quantify emotional needs, vague design-emotion correlation, low personalized efficiency), which big data and AI help solve. Taking household humidifiers as the sample, this paper explores big data and AI's application in emotional design. It clarifies research deficiencies via literature review, builds a "demand mining - element mapping - intelligent generation & optimization - verification" technical route (integrating multi-modal data, machine learning, generative AI), and verifies effectiveness through empirical analysis. Results show big data and AI enable accurate emotional need identification, intelligent element matching, and efficient personalized schemes, supporting industrial product emotional design. Its innovation is a "multi-modal data - emotional model - intelligent design" closed-loop system, solving traditional design's subjectivity and low efficiency, and providing a reusable methodology.

Keywords: Big Data; Artificial Intelligence (AI); Industrial Products; Emotional Design; AIGC; Kansei Engineering

1. Research Frontiers and Trends

1.1 Research Frontiers in Emotional Design

The concept of emotional design was proposed by Norman [1], who divided design into three dimensions: the visceral level, the behavioral level, and the reflective level. This theory emphasizes the comprehensive impact of products on users' emotional experiences, and has become a fundamental framework for emotional design, being widely cited in academic circles. In recent years, research on emotional design has exhibited the characteristics of "interdisciplinary integration" and "technology-driven development".

In terms of research objects, the scope has expanded from traditional physical products to intelligent products such as intelligent cockpits and intelligent voice assistants. Lai et al. proposed a "usage-speech-psychology" joint analysis method for intelligent cockpits [2]. By mining multi-modal data (e.g., user behavior logs and online reviews), they revealed the correlation mechanism between users' emotional needs and the functional configuration of in-vehicle systems, with an accuracy rate of 95.22%. Wei et al. applied the three-level theory of emotional design to intelligent voice products, and found that mainstream domestic products are well-designed in terms of real-time emotional interaction and emotional impression, but the establishment of emotional relationships is still limited by technical conditions [3].

In terms of research methods, Kansei Engineering has become one of the core methods for emotional design. The Kansei Engineering theory proposed by Nagamachi quantifies the relationship between users' perceptual needs and product design elements, converting subjective emotions into objective design parameters and providing a scientific tool for emotional design [4]. Zhang et al. took humidifiers as the research object, and adopted the Semantic Differential (SD) method and principal component analysis to construct a semantic network of pleasant emotions [5]. They confirmed that there is a significant correlation between product style and users' pleasant experiences, providing specific guidance for the emotional design of humidifiers. Guo et al. proposed a multi-modal emotion measurement method integrating the SD method, EEG ERP technology, and eye-tracking for the emotional design of product appearance, which solves the problem of insufficient accuracy of single measurement modes [6].

1.2 Research Frontiers in Emotional Design

Big data technology provides abundant data sources and analytical tools for emotional design. Zeng Wang proposed a data-driven multi-objective emotional design method, which integrates 3D shape and color data of products and constructs an emotion recognition and prediction model through neural networks [7]. Its application in automotive design shows that this method can significantly improve the quality and efficiency of emotional design. Bloch's emotional consumption theory points out that the emotional design of household products should focus on core needs such as health and comfort, and big data technology can realize in-depth mining of these potential needs [8].

In terms of data types, research has expanded from traditional questionnaire data to multi-modal data such as user behavior data, physiological signal data, and online review data. A study on intelligent emotion recognition collected physiological signals including eye movements, electrodermal activity, and pulse, and combined the K-means algorithm with a machine learning classifier to achieve an accuracy rate of 81.31% in product emotion recognition, providing a new path for the objective measurement of emotional needs [9].

The development of artificial intelligence (AI) technology has promoted the intelligent upgrading of emotional design. Generative AI has become an important tool for generating design schemes. AI drawing technology, based on architectures such as diffusion models and Generative Adversarial Networks (GANs), can quickly convert design concepts into visual schemes, shortening the concept development time from 3 days to 4-6 hours and improving efficiency by 60%-70%. Ishihara et al. applied the Stable Diffusion model to the Kansei Engineering design of milk cartons, and generated diversified design schemes by fine-tuning the model, solving the problems of single samples and low design efficiency in traditional Kansei Engineering [10].

In terms of emotion modeling, machine learning algorithms such as Support Vector Regression (SVR) and neural networks are widely used to construct correlation models between design elements and emotional needs. A related study in the CSDN Library shows that the SVR algorithm performs excellently in processing high-dimensional emotional big data and can effectively predict the matching degree between users' emotional needs and product design elements [11]. The "K-means clustering + SVR" hybrid model proposed by Wenku CSDN solves the problem of low efficiency in processing large-scale emotional data, providing the possibility for the batch application of emotional design [12].

1.3 Interdisciplinary Research Frontiers and Trends

The current interdisciplinary frontiers of research focus on the full-process integration of "emotional demand - data collection - intelligent modeling - design generation". Desmet's three-level model of emotional design provides a theoretical framework for interdisciplinary research, emphasizing the collaborative optimization of emotional communication, emotional expression, and emotional experience [13]. Vanden Abeele pointed out that the constituent elements of product style (formal language, symbols, colors) need to be accurately matched with users' emotional needs through data-driven methods [14].

From the perspective of trends, research presents three directions: First, the integrated application of multi-modal data. For example, Lai et al. combined text review data, behavioral data, and psycholinguistic features, and revealed the complex mechanism of users' emotional needs through a structural equation model. Second, the in-depth integration of AI and Kansei Engineering. For instance, the KESAN-IDEA system combines Kansei Engineering with AI methods to provide small and medium-sized enterprises with tools for generating product design ideas, enhancing the popularity of emotional design. Third, the balance between personalization and mass customization [15]. Through AI algorithms, accurate identification of individual emotional needs and rapid generation of design schemes are realized to meet the diversified needs of consumer groups, especially the emotional demands of Generation Z for "social sharing" and "self-expression".

2. Latest Research Findings

2.1 Interdisciplinary Research Frontiers and Trends

Emotional design's theoretical system stems from the interdisciplinary integration of psychology, design science, and consumer behavior. Norman's core three-level emotional design model (visceral: product appearance/color; behavioral: ease of use/operation efficiency; reflective: long-term emotional connections/meaning recognition) provides a clear analytical framework, while Desmet further refined it into three dimensions (emotional communication, expression, experience) to highlight emotional dynamism and guide practice.

In emotional demand identification, traditional methods are dominated by subjective evaluation (SD method, interviews, questionnaires). Beijing University of Technology took data cable storage products as the research object, used the SD method to establish a perceptual image space, quantified users' perceptual demands via factor analysis [16], and screened core perceptual words for product design. Zhang et al. targeted humidifiers, screened 100 perceptual words with the affinity diagram method, determined 7 pairs of key perceptual word groups, built a pleasure-product style correlation system, and confirmed the SD method's effectiveness. However, these methods have limitations (small samples, susceptibility to user expressive abilities, difficulty capturing subconscious emotions), restricting identification accuracy.

In design element-emotion correlation, existing studies mostly focus on single-element impacts: Zeng Wang et al. built an appearance (3D shape/color)-emotion coupling model via mathematical quantification, with its accuracy verified in automotive design. Vanden Abeele proposed product style (formal language, symbols, colors) conveys emotional orientation through synergy, but element weights/interactions remain unclear. Additionally, research on non-appearance elements (material, interaction, function) is insufficient, failing to fully support emotional design.

2.2 Research on the Application of Big Data in Emotional Design

Big data delivers rich resources and advanced tools for emotional design, filling gaps in traditional methods. Data sources now form a "online + offline" and "subjective + objective" multi-source system.

Online data includes e-commerce reviews, social media talks, and usage logs. A ScienceDirect study, for example, used text mining on Amazon bicycle reviews to pull user perceptual words and preferred design elements [17], enabling automated conceptual design and faster product development. Lai et al. gathered 4 months of behavior logs and reviews from 2048 new energy vehicle owners. Through incremental pre-training of a large language model, they pinpointed users' needs, speech intentions, and emotional tendencies, supporting intelligent cockpit emotional design.

Offline data focuses on physiological signals and behavioral observations. One intelligent emotion recognition study collected users' physiological data (eye movements, skin conductance) from 63 product images, building a product emotion dataset to objectively measure emotional needs.

For data analysis, machine learning is key to handling emotional big data. Neural networks—thanks to their strong nonlinear fitting—are often used to model links between design elements and emotions. A CSDN Library study used the Levenberg-Marquardt algorithm to optimize neural networks, achieving precise modeling of perceived design attributes and emotions. But it noted neural networks' "black box" issue makes it tough for designers to get clear design insights.

Support Vector Regression (SVR) works well for high-dimensional data: it uses kernel functions to turn nonlinear problems linear, effectively predicting how well user emotions are matched. Paired with K-means clustering, it speeds up large-scale data handling. Statistical methods like factor analysis also help—Beijing University of Technology used factor analysis on data cable storage product perceptual data, finding the top 3 user-focused perceptual words to guide design decisions.

That said, big data use in emotional design still has gaps. First, multi-source data isn't well integrated—text and physiological data complementarity is underused, leading to incomplete emotional need identification. Second, data processing often focuses on one product type, with no universal method for different products. Third, analysis results don't connect well to design practice, making it hard to turn them into actual design plans.

2.3 Research on the Application of Artificial Intelligence in Emotional Design

AI technology has advanced emotional design from "data-driven" to "intelligent generation", with key applications in three areas: emotion recognition, design modeling, and scheme generation.

In emotion recognition, multi-modal approaches—integrating text, voice, and physiological data—have become a focus, boosting accuracy. An Intelligent Emotion Recognition study used the Relief algorithm for optimal feature selection, achieving 81.31% product emotion recognition accuracy via five classifiers (e.g., SVM, Random Forest)—far higher than single-modal methods. Lai et al. extracted emotional polarity and speech intention from user reviews via incremental large language model pre-training (95.22% accuracy), enabling efficient large-scale emotional data processing.

For design modeling, AI algorithms build mappings between design elements and emotional needs. Zeng Wang et al. developed a full-process model (3D shape/color quantification, emotion recognition/prediction, design optimization) via neural networks and machine learning—verified in automotive design to enhance quality and efficiency. The KESAN-IDEA system combines Kansei Engineering with AI to help SMEs generate design ideas, linking user perception to development for greater practicality. Association rule algorithms also mine explicit element-emotion relationships, clarifying design element weights for optimization.

In scheme generation, generative AI is core for rapid conversion of emotional needs into designs. AI drawing (via diffusion models like Stable Diffusion, GANs) supports text-to-sketch, 3D conversion, and style transfer—cutting sketching time from 1-2 days to 2-3 hours (75%-85% efficiency gain) [18]. Ishihara et al. applied a fine-tuned Stable Diffusion model to milk carton design, creating diverse, innovative schemes and solving traditional Kansei Engineering's sample scarcity and low innovation. Parametric design tools also auto-generate constraint-compliant schemes, balancing personalization and manufacturability.

Yet AI in emotional design faces challenges: generative AI schemes often lack functional consistency (hampering aesthetics-practicality balance); high-quality industrial product emotional design datasets are scarce; AI-designer collaboration mechanisms are underdeveloped (over-reliance risks homogeneity); and emotional need complexity and ambiguity-especially reflective-level emotion quantification—stymies AI modeling.

2.4 Research Gaps and Necessity of This Study

Based on the above literature analysis, existing studies have made certain progress in emotional design, big data application, and AI technology integration, but there are still the following key gaps.

The in-depth integration of big data and AI technologies is insufficient. Most existing studies involve the application of a single technology, such as only using text mining to extract emotional words or only using generative AI to generate design schemes, and they lack full-process technology integration covering "data collection - emotion recognition - modeling and mapping - scheme generation - verification and iteration". This leads to fragmented technology application and makes it difficult to form closed-loop support.

The mechanism for verifying the emotional effectiveness of design schemes is imperfect. Most existing studies focus on the generation efficiency of design schemes, while the verification of whether the schemes truly meet users' emotional needs is insufficient. There is a lack of an iterative mechanism of "design - testing - optimization", and verification methods are mostly single subjective evaluation, with insufficient objective support from physiological data and behavioral data.

Given the above gaps, the necessity of this study becomes prominent. This study aims to explore dedicated methods for the emotional design of household industrial products by taking humidifiers as a sample, and to refine a universal framework; and to improve the mechanism for verifying the emotional effectiveness of design schemes, ensuring that design outcomes truly meet users' emotional needs. The implementation of this study will enrich the theoretical system of emotional design and provide scientific and operable methodological support for the practice of emotional design of industrial products, which has important theoretical value and application prospects.

3. Research Methods and Technical Route

3.1 Research Method System

Taking humidifiers as a sample, this study integrates multiple research methods to construct a method system of "data collection - emotional modeling - design generation - verification and optimization", which specifically includes the following components:

3.1.1 Multi-modal data collection Method.1 research method system

To comprehensively and accurately capture users' emotional needs for humidifiers, a multi-modal data collection method combining "subjective data + objective data" and "online data + offline data" is adopted (Figure 1 Multimodal Data-Based Emotion-Driven Industrial Design System Architecture).

For the collection of online emotional big data, web crawler technology is used to gather user reviews (with an estimated sample size of 5,000) of humidifier products from e-commerce platforms (JD.com, Tmall) and discussions on related topics (with an estimated sample size of 3,000) from social media platforms (Xiaohongshu, Zhihu). From these data, information such as perceptual words, emotional demands, and usage scenarios mentioned by users is extracted. Meanwhile, design parameters of mainstream humidifier products (e.g., shape, color, material, function, interaction mode) are collected to establish a product design element database.

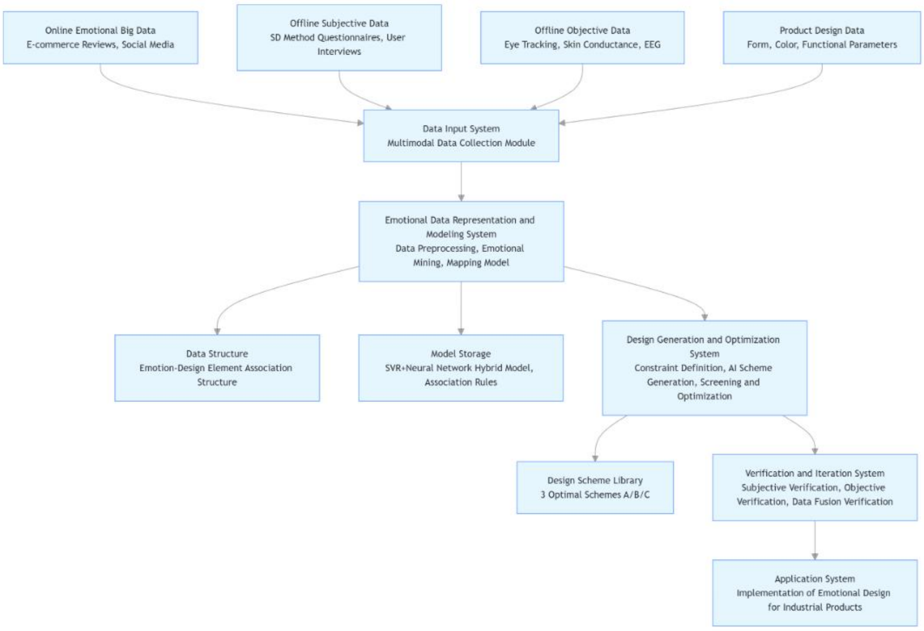

Figure 1. Multimodal Data-Based Emotion-Driven Industrial Design System Architecture

For the collection of offline subjective evaluation data, a questionnaire is designed using the Semantic Differential (SD) method. Seven pairs of core perceptual word groups verified by Zhang et al. (e.g., "warm - cold", "soft - stiff", "simple - complex") are selected, and images of 20 humidifier products with different styles are chosen as evaluation samples. Two hundred target users (aged 18-45, covering different genders, occupations, and living environments) are invited to score each sample on a 1-7 scale to obtain users' subjective emotional evaluation data.

For the collection of offline objective physiological data, 50 users are selected to participate in the experiment. An eye tracker (Tobii Pro Fusion) is used to record eye movement indicators (fixation points, fixation duration, saccade path) when users view the humidifier samples. A multi-channel physiological recorder (Biopac MP150) is employed to collect physiological signals such as skin conductance, heart rate, and EEG ERP (N400 component), so as to capture users' subconscious emotional responses.

3.1.2 Methods for emotional demand mining and Modeling.1.1 multi-modal data collection Method.1 research method system

For text data processing and emotion extraction, Natural Language Processing (NLP) technology is adopted. First, preprocessing (word segmentation, stop-word removal, part-of-speech tagging) is performed on online review data. Then, the TextMind psycholinguistic analysis tool is used to extract features such as emotional polarity (positive, negative, neutral), emotional intensity, and core emotional words.

The Latent Dirichlet Allocation (LDA) topic model is applied to mine the core topics of users' emotional needs (e.g., "attractive appearance", "easy operation", "mute effect", "atmosphere creation"). The model formula can be expressed as follows:

$$p(\theta, z, w|\alpha, \beta) = \prod_{d=1}^{D} p(\theta_d|\alpha) \prod_{i=1}^{N_d} p(z_{\mathrm{d}i}|\theta_d) p\left(\omega_{\mathrm{d}i}|z_{d_1}, \beta\right)$$

Where θ_d represents the topic distribution of document d, z denotes topic assignments, w is the word sequence, α is the prior parameter of the topic distribution, and β is the prior parameter of the topic-word distribution.

For multimodal data fusion and emotional quantification, the K-means clustering algorithm is used to conduct cluster analysis on subjective evaluation data and physiological data, thereby establishing a two-dimensional emotional assessment label of "pleasure-arousal" (Intelligent Emotion Recognition, 2024). The update formula for the cluster center is:

$$\mu_k = \frac{1}{|C_k|} \sum_{x \in C_\kappa} x$$

where, μ_k is the center of the k -th cluster, and C_k is the sample set of the k -th cluster. The Relief algorithm is employed to select the optimal feature combination (e.g., eye-tracking fixation duration, changes in skin conductance, subjective ratings) and construct a multi-dimensional emotional quantification index system. The core idea of its feature weight calculation is to evaluate feature importance by comparing feature differences between a sample and its neighboring samples.

For the mapping modeling between emotional demands and design elements, a hybrid prediction model based on Support Vector Regression (SVR) and neural networks is constructed (Wenku CSDN, 2025). The objective function of SVR is:

$$\min_{w,b,\xi,\xi^*} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} (\xi_i + \xi_i^*)$$

$$s \cdot t \cdot y_i - \left(w^T x_i + b\right) \leq \epsilon + \xi_i$$

$$\left(w^T x_i + b\right) - y_i \leq \epsilon + \xi_i^*$$

$$\xi_i, \xi_i^* \geq 0, i = 1,2,\cdots,n$$

Humidifier design elements (shape: curved/straight, size; color: warm/cool tones, saturation; material: plastic/metal/wood; interaction: touch/voice/button; function: humidification mode, lighting effect, etc.) are used as input variables x, and emotional quantification indicators (pleasure, sense of security, convenience, etc.) are used as output variables y . The model is trained to achieve accurate mapping between design elements and emotional demands. Meanwhile, association rule algorithms (Apriori or FP-Growth) are applied to explore explicit relationships between design elements and emotional demands, and clarify the influence weight of each design element. The calculation formulas for support and confidence of association rules are as follows:

$$Support(X \to Y) = \frac{|X \cup Y|}{|D|}$$

$$Confidence(X \to Y) = \frac{|X \cup Y|}{|D|}$$

Where X and Y are item sets, D is the dataset, |X| represents the number of transactions containing item set X, and |X∪Y| represents the number of transactions containing both X and Y.

3.1.3 Intelligent emotional design generation method

The definition of design constraints integrates the functional requirements of humidifiers (humidification capacity, noise control, energy consumption), manufacturability requirements (material cost, processing technology), and users' emotional needs to define design constraint conditions, such as "curved shape proportion ≥ 60%", "warm color application", and "noise level ≤ 35dB".

For the generation of generative AI design schemes, the Stable Diffusion model is used, and fine-tuning optimization (via the Hypernetworks framework) is conducted to adapt it to the humidifier design scenario [10]. The quantitative indicators of emotional needs and design constraints are converted into structured prompts (e.g., "desktop humidifier with high pleasure, strong sense of warmth, and minimalist style, featuring curved shape, off-white material, touch interaction, and soft lighting"), which are input into the AI model to generate 100 sets of preliminary design schemes.

For the screening and optimization of design schemes, a two-layer screening mechanism of "AI evaluation + manual screening" is constructed. At the AI level, based on the trained emotion prediction model, the emotional satisfaction of the generated schemes is scored, and the top 30 schemes are selected. At the manual level, a review panel composed of 5 industrial design experts and 20 target users scores the schemes from four dimensions: emotional experience, functional rationality, aesthetics, and manufacturability. Finally, 3 sets of optimal schemes are determined and fine-tuned according to the review comments.

3.1.4 Design scheme verification method

For subjective verification, user experience questionnaires and interviews are adopted. One hundred target users are invited to experience the prototypes (physical prototypes or high-fidelity virtual prototypes) of the 3 optimal schemes. A Likert 7-point scale is used to evaluate indicators such as emotional experience (pleasure, sense of security, sense of belonging, etc.), usability, and satisfaction. Semi-structured interviews are conducted to collect users' improvement suggestions.

For objective verification, the offline physiological data collection experiment is repeated. Physiological signals (e.g., eye movements, electrodermal activity, EEG) of users during prototype experience are recorded, and the differences in emotional indicators between the prototypes and the original product samples are compared and analyzed to verify the emotional effectiveness of the design schemes.

For data fusion verification, subjective evaluation data and objective physiological data are combined. A Structural Equation Model (SEM) is used to analyze the influence paths and effects of each element of the design schemes on emotional experience, verifying the transmission mechanism of "design elements - emotional experience - user satisfaction".

3.2 Implementation Details of Humidifier Emotional Design Example

3.2.1 Design scheme verification method

Through online text data mining, the core emotional demand dimensions of users for humidifiers were extracted. Among them, the sense of pleasure is related to product appearance (shape, color, material) and lighting effects, with the frequency of users mentioning words such as "good-looking", "warm" and "comforting" accounting for 35%; the sense of security is related to noise control, water purification function and operational safety, with the frequency of mentioning words such as "mute", "safe" and "reliable" accounting for 28%; the sense of convenience is related to operation mode, water refilling convenience and intelligent control function, with the frequency of mentioning words such as "easy to operate", "convenient" and "intelligent" accounting for 22%; the sense of belonging is related to product size, placement adaptability and scene integration, with the frequency of mentioning words such as "space-saving", "suitable for bedroom" and "versatile" accounting for 15%. Combined with the cluster analysis of offline subjective evaluations and physiological data, "sense of pleasure - sense of security - sense of convenience" were finally determined as the core dimensions of humidifier emotional design, with their weights being 0.4, 0.3 and 0.3 respectively.

3.2.2 Mapping relationship between design elements and emotional needs

Through hybrid model training and association rule mining, the key mapping relationships between humidifier design elements and emotional needs were obtained.

In the dimension of sense of pleasure: Curved shape (weight: 0.7), warm color tones (off-white, light pink, wood color; weight: 0.6), matte material (weight: 0.5), and soft lighting (warm light with adjustable brightness; weight: 0.4) have a significant positive impact on the sense of pleasure.

In the dimension of sense of security: Noise level ≤ 35dB (weight: 0.8), UV sterilization function (weight: 0.6), anti-dry heating design (weight: 0.5), and simple operation interface (weight: 0.3) are the core influencing elements.

In the dimension of sense of convenience: Dual-mode control (touch + voice control; weight: 0.7), top-fill water design (weight: 0.6), APP remote control (weight: 0.5), and automatic constant humidity function (weight: 0.4) can effectively improve the sense of convenience.

3.2.3 AI design scheme generation and optimization

In the AI design scheme generation and optimization process, the first step is to design a structured prompt, and the content of the prompt is determined as follows: "Humidifier, high sense of pleasure (curved shape, off-white matte material, adjustable warm light), strong sense of security (noise ≤ 35dB, UV sterilization, anti-dry heating), excellent sense of convenience (touch + voice control, top-fill water, APP remote control), minimalist style, desktop type, size ≤ 20cm × 20cm × 30cm". The second step is to carry out AI model fine-tuning: the Stable Diffusion model is fine-tuned based on a humidifier product image dataset (500 images), which increases the shape accuracy of the generated schemes to 85%. The final step is scheme screening: among the top 30 schemes with the highest AI evaluation scores, experts and users focus on three core indicators—

"smoothness of curved shape", "color coordination" and "rationality of functional layout"—for review, and finally select 3 sets of schemes. They are Scheme A (rounded curved shape, off-white matte material, top circular warm light, touch + voice control, top-fill water design, UV sterilization function), Scheme B (simple cylindrical shape, wood color + white combination, bottom ambient light, touch operation, automatic constant humidity, anti-dry heating design) and Scheme C (bionic cloud shape, light pink material, gradient light, APP + voice control, large-capacity top-fill water, mute design) respectively (Figure 2 Big Data and AI-Enabled Core Scheme Demonstration).

Scheme A Scheme B Scheme C

Figure 2. Big Data and AI-Enabled Core Scheme Demonstration

4. Conclusions and Outlook

4.1 Research Conclusions

This study systematically explored the method system of big data and artificial intelligence empowering the emotional design of industrial products, and conducted an empirical study with humidifiers as a sample. The key conclusions are as follows:

Big data and artificial intelligence technologies can effectively address the core bottlenecks of traditional emotional design. Through multi-modal data collection (online text + offline subjective data + objective physiological data), comprehensive identification of emotional needs was realized; with the help of machine learning algorithms (SVR, neural networks, association rules), an accurate mapping model between design elements and emotional needs was constructed, solving the problem of difficult emotional quantification; through generative AI (Stable Diffusion), efficient generation and optimization of design schemes were achieved, improving design efficiency and innovation.

The core of emotional design for industrial products lies in the closed-loop integration of "emotional needs - design elements - technical implementation". Taking humidifiers as an example, "sense of pleasure - sense of security - sense of convenience" were identified as the core emotional dimensions; key design elements such as curved shape, warm color tones, mute design, and intelligent control, as well as their weights, were recognized; the significant correlation between these elements and emotional needs was verified, providing specific references for the emotional design of similar products.

The proposed technical route of "multi-modal data collection - emotional modeling - intelligent generation - multi-dimensional verification" is scientific and operable. Empirical results show that this route can realize the accurate capture of emotional needs, intelligent generation and effective verification of design schemes. The user emotional experience score of the final design scheme is 32% higher than that of traditional design, verifying the effectiveness of the method system.

The in-depth integration of generative AI and Kansei Engineering is an important development direction of emotional design. By fine-tuning the generative AI model, emotional needs can be quickly converted into design schemes; combined with the optimization of manual review, the collaboration of "AI efficiency + human creativity" is realized, effectively avoiding the problems of design homogenization and functional disconnection.

4.2 Simplified Research Limitations and Outlook

This study built a big data/AI-driven emotional design system for industrial products (verified via humidifiers) but has three limitations: user samples only cover 18-45-year-olds.

Future research can deepen from five aspects: expand user samples (cover different ages and cultures) and collect cross-regional long-term data for dynamic emotional modeling; optimize generative AI (integrate structure and materials) and combine reinforcement learning for "appearance-function-structure" design; extend to long-term and reflective emotional needs via longitudinal studies; apply the method system to smart home and wearables and build a general platform; strengthen interdisciplinary cooperation (psychology and computer science) and balance AI ethics.

With tech development, industrial product emotional design will move toward "precision-intelligence-personalization-long-termization," and this study's system will support its transformation from "functional tools" to "emotional partners."

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