Construction and Optimization of an Artificial Intelligence-Assisted Kansei Engineering Product Design Mapping Model

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Abstract. This paper systematically summarizes the application of artificial intelligence technology in Kansei engineering research, mainly including three aspects: emotional imagery acquisition, product design feature extraction, and mapping model construction. AI technology can quickly and accurately obtain users' emotional imagery, extract product design features, and establish a mapping relationship between user emotions and product features, thereby improving the efficiency and quality of emotional product design. The article points out that there are still certain limitations in the current application of AI in Kansei engineering, and future development directions include multi-expert collaboration, the application of virtual reality technology, and the integration of generative AI. This paper provides a useful reference for the application of AI technology in Kansai engineering research.

Keywords: Artificial Intelligence, Kansei Engineering, Product Design

1 Introduction

Kansei Engineering, also known as Sensibility Engineering, is a product design methodology that emphasizes the close connection between product design and users' feelings, emotions, and experiences[1]. The goal of Kansei Engineering is to create products that are not only functionally complete but also emotionally resonant with users[2]. The application of Artificial Intelligence (AI) in Kansei Engineering is a relatively new research field that has shown great potential in enhancing product design and user experience[3][4]. AI technology can quickly and accurately capture users' emotional imagery, extract product design features, and establish a mapping relationship between user emotions and product features, thereby improving the efficiency and quality of emotional product design[5][6]. This article systematically summarizes the application of AI technology in Kansei Engineering research and its future development trends from three aspects: emotional image acquisition, product design feature extraction, and mapping model construction.

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2 Emotional Imagery Acquisition

In Kansei engineering research, accurately capturing users' emotional imagery is a crucial step[7]. This process usually involves manual surveys using Kansei vocabulary, selection and classification of product feature samples, design and reliability calculations of questionnaires, and subsequent data testing and analysis[8]. Methods such as semantic differential, hierarchical analysis, and quantification theory are widely used. However, due to the diversity and ambiguity of emotions and language, manual methods often come with subjective errors, and certain emotional changes are nonlinear, making traditional linear regression methods inadequate for research needs.

In order to address these issues, the field of Kansei Engineering has started to incorporate computer technology and machine learning tools such as Support Vector Machines, Support Vector Regression, Softmax Regression, k-Nearest Neighbors, Classification and Regression Trees, Multiple Regression Models, Logistic Regression Analysis, Deep Belief Networks, Multilayer Perceptron (MLP) Artificial Neural Networks, Long Short-Term Memory Neural Networks, and Deep Learning to achieve more effective classification and fitting. Particularly, deep learning has shown outstanding performance in handling massive data due to its ability to autonomously extract relevant feature information and capture the nonlinear and complex relationships within the data. For instance, LI and colleagues used various machine learning algorithms to extract and quantify users' emotional responses from online reviews; YAN and colleagues proposed a method for uncertain Kansei Engineering for campus delivery services, utilizing polynomial logistic regression to establish uncertain relationships between design attributes and emotional attributes; WANG and colleagues introduced a heuristic deep learning method, combining rule-based extraction with deep learning results, achieving accurate classification of multiple emotional attributes.

In addition to machine learning techniques, research has also started to combine physiological signal measurement and psychological cognitive measurement, using sensors, computers, and other technologies for quantitative studies on users' Kansei imagery, to enhance the precision of data collection and recognition. Common methods include EEG (Electroencephalography), ERP (Event-Related Potential), eye-tracking, facial expression systems, and fMRI (Functional Magnetic Resonance Imaging). SHI and colleagues even proposed a method for value-based Kansei modeling integrated with fMRI.

Although questionnaires and physiological signal measurements provide valuable data, they are often labor-intensive and limited by factors such as data scale and testing environment. Therefore, the research trend has shifted towards using online user reviews for sentiment analysis, a method proposed by NASUKAWA and YI in 2003. By analyzing massive amounts of user evaluations, this approach can reveal users' attitudes and emotions towards product attributes, quantify preferences for products and competitors, and guide product improvements. For example, LAI and colleagues used internet data to analyze user demands for the appearance design of new energy vehicles; JIAO and colleagues proposed a method to extract Kansei knowledge from online reviews, establishing a relationship model between product design features and user perception evaluations; LIU delved into sentiment analysis and proposed various solutions.

As user expression shifts from text to emojis, image-text integration, and videos, sentiment analysis of these new forms of information has become a new research focus. SU and colleagues used Convolutional Neural Networks to predict user opinions based on image data. Compared to traditional questionnaires and physiological signal tests, sentiment analysis based on big data can track user emotional changes in real-time, predict product trends, provide decision support for designers, promote the development of data-driven, real-time Kansei Engineering methods, and achieve system self-improvement and intelligent design.

3 Product Design Feature Extraction

Effective feature extraction in product design plays a crucial role in enhancing the accuracy of the mapping model between user imagery and product design features, as well as ensuring the transmission of specific emotions to new products. This process mainly involves two stages: sample collection and feature element extraction. Firstly, product samples are collected and categorized to determine representative design features. Secondly, various methods such as morphological analysis, appearance genetics, eye-tracking experiments, parametric modeling, and physical measurement are employed to decompose design features to obtain specific design elements, encompassing both qualitative and quantitative extraction methods. However, current sample collection and product feature annotation primarily rely on the experience and intuition of designers. Defining product features through parametric methods is not only operationally complex and costly but also limited in the variety and quantity of product features obtained, failing to comprehensively describe product feature factors. Therefore, using artificial intelligence technology to assist in extracting product design features has become a future development trend.

The processing of existing samples can be achieved by combining computer vision, image processing technology, and deep learning to classify product samples and extract features. Common image classification tools include Radial Basis Function Neural Networks, Elman Neural Networks, General Regression Neural Networks, BP Neural Networks, Convolutional Neural Networks, and Deep Residual Networks. For instance, CHEN and colleagues established an efficient cockpit emotion evaluation system, applying neural networks to construct emotional models for assessing the emotional prediction of aircraft cockpit interior designs; ISHIHARA and colleagues used two-dimensional Fast Fourier Transform and Convolutional Neural Networks to analyze the relationship between texture features and user emotions; Pei Huining and others proposed a morphological design decision-making model based on capsule networks, using convolutional layers and dynamic routing algorithms to generate main capsules with rich semantic features, thereby improving the accuracy of product morphological design decisions.

The emergence of generative AI has made it possible to use artificial intelligence technology to generate corresponding sample features (AI-Generated Content, AIGC). AIGC enables transformations between text and images, as well as between images, offering higher efficiency, lower costs, and a broader scope than manual methods. For example, tools like DALL·E2, Stable Diffusion, and Midjourney can generate corresponding images based on user descriptions and provide open-source component plugins for personalized use, helping designers quickly obtain a large number of creative images with diverse styles in a short time, and comprehensively explore product-related design features.

Additionally, the use of three-dimensional measurement and computer vision technology for the quantitative extraction of product features is also noteworthy. Computer vision technology has significant advantages in measuring product morphological indicators, not only improving measurement efficiency and accuracy but also enabling automation, non-contact, and data traceability. For instance, three-dimensional visual measurement technology can obtain morphological data of three-dimensional objects, objectively describing object forms, and has been widely used in fields such as precision manufacturing, automotive, aerospace, healthcare, and cultural relics protection.

In summary, artificial intelligence technology can assist designers in automatically generating, analyzing, and measuring different products and design features, supporting the construction of mapping models, thereby significantly improving work efficiency and accuracy, and helping to create products with greater emotional appeal and user satisfaction.

4 Mapping Model Construction

The construction of mapping models is primarily used to simulate the mapping relationship between users' Kansei imagery and product design elements, and it is the core of emotional translation in product design. Early model construction mainly relied on manual methods, such as category recognition (Type I Kansei), or with the help of mathematical and statistical tools like linear regression and quantitative theory (Type I), as well as computer programs like genetic algorithms and fuzzy logic. Machine learning technologies, in particular, have been widely adopted due to their ability to automatically analyze and process data, improve work efficiency, reduce the risk of human error, and enhance the reproducibility of results. These technologies include Classification and Regression Trees, Decision Trees, Rough Set Kansei, Fuzzy Linguistics, Logistic Regression, Grey Fuzzy Models, Random Forests, Naive Bayes, Support Vector Regression, Association Rule Learning, Ridge Regression, Multilayer Perceptrons, Support Vector Machines, and BP Neural Networks. For example, DING and colleagues proposed a product color emotion design evaluation method based on XGBoost; SAKORNSATHIEN and colleagues used decision tree classification technology combined with K-means technology for user style and preference classification; XUE and colleagues proposed a hybrid research method by constructing GRA-Fuzzy logic submodels for product form and color design; LI and colleagues proposed a posterior preference linking method for the multi-objective optimization problem of satisfying various emotional responses; LIN Li and colleagues established a product form Kansei Engineering model combining eye-tracking weighting, EEG imagery cognition, and ridge regression; LIU Yuelin and colleagues proposed an imagery modeling design method using triangular fuzzy theory and BP Neural Networks.

However, traditional algorithms have limitations in handling high-dimensional and nonlinear data. Although artificial neural networks like BP Neural Networks are widely used in building mapping models, they have limitations in learning speed, solving multi-input problems, avoiding local optimal solutions, and expressing nonlinear data. Deep learning networks, such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Deep Residual Learning Networks (ResNet), and Self-Organizing Maps (SOM), overcome these limitations with their automatic feature learning capabilities and stronger nonlinear processing abilities. For instance, CAO Shuyuan and colleagues proposed a mechanical product Kansei evaluation method combining online product reviews and TextCNN; KIM and colleagues used Self-Organizing Maps (SOM) to extract user emotional variables from online reviews for classification.

In the future, deep learning algorithms such as transfer learning and deep reinforcement learning may also be applied to mapping model construction. Transfer learning reduces training costs by applying knowledge learned from one task or domain to another. Deep reinforcement learning allows the model to self-optimize according to user emotions and sensory changes by setting reward signals. After model construction, researchers typically use intelligent algorithms such as genetic algorithms, swarm intelligence algorithms, evolutionary algorithms, fuzzy algorithms, deep convolutional generative adversarial networks, spiking neural networks, and multi-objective optimization algorithms for optimization and refinement. For example, WANG and colleagues used BPNN to identify the relationship between design variables and user needs, and employed the Non-Dominated Sorting Genetic Algorithm-II as a multi-objective evolutionary method; GAN and colleagues introduced Deep Convolutional Generative Adversarial Networks (DCGAN) into Kansei Engineering methods; DING and colleagues used Convolutional Neural Networks and Search Neural Networks to establish a complex correlation model between product color and user emotional imagery.

Overall, the combination of machine learning technologies and related optimization algorithms significantly enhances the effectiveness, accuracy, and reliability of mapping model construction, helping designers and researchers gain a deeper understanding of user emotional needs, thus expanding the innovation potential in this field.

5 Issues and Prospects

Through in-depth analysis and comparison of the current state of Kansei Engineering research both domestically and internationally, it is evident that the application of artificial intelligence technology in Kansei Engineering is increasingly prevalent. Future trends in Kansei Engineering will focus on establishing multi-expert collaboration technologies, guided by design thinking and methods, utilizing artificial intelligence means to achieve a comprehensive and accurate acquisition of user Kansei imagery, deconstructing and quantifying design features, and establishing more precise mapping models. At the same time, combining various automatic generation mechanisms will promote the intelligent development of the entire Kansei design process.

The use of advanced data mining and natural language processing technology, computer vision applications, and the fusion of multi-modal physiological and psychological signals can widely collect and accurately extract real user Kansei imagery, establishing large-scale, high-quality databases. Such technologies can capture and track changes in user emotional imagery in real-time, providing flexible data selection for model training. However, the application of sentiment analysis is still in its initial stage, mainly focusing on technical polarity classification, lacking attention to emotional details and product specifics. The construction of sentiment imagery dictionaries still requires manual intervention to improve accuracy and suffers from issues like strong subjectivity and low timeliness. Additionally, language description differences among different research objects or fields lead to poor generalizability, usually requiring separate construction.

In the construction of Kansei Engineering models, there is currently a lack of research on the differentiation and correlation between different types of users. Analyzing the differences among user groups and integrating user characteristics into the model is crucial for improving model applicability, which also means more precise data is needed. In the process of applying machine learning to build Kansei models, issues like overfitting and underfitting are often encountered. Therefore, in addition to obtaining a large amount of data reflecting users' true imagery, it is necessary to select appropriate algorithmic models and training techniques, requiring researchers to possess expertise and incurring high training costs. Improving the generality of models to enhance training efficiency has become a practical issue. Notably, meta-reinforcement learning algorithms reduce the learning cost for new tasks by finding knowledge correlations between different products, effectively improving model learning speed, and providing broader, more flexible application possibilities for Kansei Engineering.

As the field of deep learning continues to advance, the integration of virtual reality (VR) and augmented reality (AR) technologies into Kansei Engineering research has opened up new possibilities. By creating immersive virtual environments, researchers can simulate users' emotional responses to various design configurations. The implicit psychological reactions that occur during human-artifact interactions are influenced by a multitude of background factors, and the combination of AR and VR can help reduce the interference users may experience during testing. Compared to traditional methods like sketches and images, VR-based prediction models are more accurate and reliable in predicting user emotional preferences.

After a period of technological accumulation and iteration, generative AI, exemplified by ChatGPT, has entered a phase of rapid development, heralding a new wave of the "AI revolution." The advent of AI-Generated Content (AIGC) has significantly lowered the threshold for independent creation and content production, with applications in code generation, text Q&A, and image creation, among others. When applied to Kansei Engineering, AIGC enables the rapid creation of a large number of product samples for user research. This facilitates a deeper understanding of customers' emotional associations and perceptions of different products, aiding in the improvement and iteration of product design.

6 Conclusion

With the development of generative AI technologies such as ChatGPT and Midjourney, the focus of Kansei Engineering research is gradually shifting towards a deeper understanding and definition of user emotional needs, stimulating creative thinking, integrating emotional models, and focusing on the application of AI in input details. Looking ahead, with AI's powerful capabilities in data collection, integration, and design expression, the design and development of emotional products will become more comprehensive, accurate, and efficient, pushing Kansei Engineering towards deeper and broader development.

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