APEM journal
Advances in Production Engineering & Management
Volume 21 | Number 2 | June 2026 | pp 221–238
https://doi.org/10.14743/apem2026.2.570
ISSN 1854-6250
Journal home: apem-journal.org
Original scientific paper

A data-driven framework for intelligent product development of wearable health monitoring devices using deep learning

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ABSTRACT

The rapid growth of artificial intelligence (AI) has shifted the development of wearable health monitoring devices toward intelligent design. However, conventional approaches still rely heavily on experience, involve inefficient user requirement acquisition, and lack systematic support for innovation. To address these limitations, this study proposes a data-driven framework for intelligent product development that integrates deep learning, Kansei Engineering, and TRIZ theory. The framework establishes an AI-assisted workflow comprising online data acquisition, requirement identification, knowledge mapping, concept generation, and engineering optimization. First, web crawlers collect user reviews and product images. A convolutional neural network (CNN) identifies form features, while a generative adversarial network (GAN) generates diverse design concepts. Kansei Engineering then maps user requirements to design elements, and TRIZ theory resolves engineering contradictions to support systematic optimization. A case study of smart health watches, using a dataset of nearly 30,000 images and more than 12,000 reviews, demonstrates that the framework can effectively automate requirement extraction, concept generation, and design optimization. Compared with traditional experience-driven methods, the proposed framework significantly improves decision-making efficiency and supports product innovation. This study extends the application of deep learning to engineering design support and provides a transferable methodology for data-driven intelligent product development.

ARTICLE INFO

Keywords:
Intelligent product development;
Data-driven design;
Engineering design support;
Artificial intelligence;
Generative adversarial networks;
Deep learning;
Wearable health monitoring devices;
Sensory engineering;
AI-assisted product development

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Article history:
Received 30 October 2025
Revised 30 June 2026
Accepted 2 July 2026

1. Introduction

With the rapid advancement of wearable technology and increasing health awareness, smart health monitoring devices such as smartwatches and bracelets have become integral to daily life. These devices enable real-time tracking of health metrics such as heart rate, blood pressure, and blood oxygen levels, empowering users to manage their health proactively [1]. However, despite the increasing capabilities of these devices, many fail to meet user needs and aesthetic preferences, resulting in a disconnect between product development and user experience [2].

Current research primarily focuses on improving the technical performance of wearable devices, such as using smart sensors and artificial intelligence for in-depth analysis of health data to improve the effectiveness of healthcare services. However, a mature data-driven design methodology for effectively transforming massive amounts of user data into engineering design decisions and establishing a systematic correlation between user needs, product design elements, and innovative design is still lacking. Zaied *et al.* [3] reviewed the application of electronic health records (EHR) in electronic health systems and discussed their use in disease diagnosis, patient health monitoring, clinical decision support systems (CDSS), etc. In addition, the authors explored the role of EHR in data mining and analyzed issues related to medical data security, privacy protection, data interoperability, etc. While these studies have made significant progress in health data analysis and medical decision support, research remains limited on how to fully utilize user behavior data and online evaluation data to support product design decisions and systematically transform user needs into design elements.

At present, with the development of technologies such as data mining, deep learning, and natural language processing, research on data-driven design is shifting toward mining knowledge of practical value for design [4]. Researchers are increasingly using data-driven design methods, including perception engineering and cognitive science [5]. However, traditional laboratory data collection methods are time-consuming and have potential limitations. Therefore, large volumes of real-world data available on the Internet offer a promising alternative [6]. Li *et al.* [7] improved the efficiency and accuracy of customer demand analysis by using techniques such as text mining, word association models, importance ranking, and quality function deployment. With the development of artificial intelligence technology, intelligent product development based on big data has received increasing attention, aiming to accurately identify needs by analyzing massive user data, support rapid product updates, and improve market competitiveness and user satisfaction [8]. Recent studies have further demonstrated that integrating AI, IoT technologies, and real-time data analysis can significantly enhance intelligent decision support and engineering optimization under data-driven frameworks [9]. These technologies provide technical support for the perceptual image mining module in perception engineering, which can reduce inaccuracies associated with the manual collection of perceptual vocabulary and image data and capture consumers' needs more objectively and accurately.

In terms of emotional design, perceptual engineering can transform users' perceptual needs (aesthetics, comfort, pleasure, etc.) into specific product design elements through scientific methods [10]. By systematically translating these perceptual needs into design elements, perceptual engineering provides an important theoretical basis and practical guidance for humanized and emotional design. Golondrino *et al.* [11] proposed a system combining sentiment analysis and fuzzy logic to evaluate user satisfaction more accurately. The system aims to overcome the limitations of traditional satisfaction evaluation methods that rely solely on quantitative questionnaire items by introducing open questions to collect user opinions and combining sentiment analysis technology to process text data, thereby obtaining more comprehensive information on user satisfaction. Perceptual engineering and TRIZ theory offer distinct advantages in user demand analysis and innovative design conflict resolution, respectively. Combining these two approaches offers considerable value for the innovative design of wearable smart health monitoring equipment.

Deep learning technologies, represented by deep convolutional neural networks (DCNNs), have achieved breakthrough results in face recognition, image recognition, and computer vision for autonomous driving [12]. Maheswari and Rajesh [13] proposed the SMDTR-CNN method based on deep learning to fuse and classify remote sensing images, significantly improving classification accuracy and the Kappa coefficient. Kalaiarasu and Ranjeeth Kumar [5] used deep learning algorithms for sentiment analysis to improve the accuracy and efficiency of sentiment classification, thereby improving the classification of emotional tendencies. Chai *et al.* [14] developed a GAN-based automatic coloring model for shoe design sketches, but their model did not fully consider consumers' emotional preferences. Quan *et al.* [15] proposed a product style transfer method that combines deep learning and sensory engineering and can automatically generate new design schemes with specific styles; however, this method only changes the product style and cannot create new product forms. Niu *et al.* [16] further proposed a defect data enhancement method based on SDGAN, which synthesized high-quality defect images through generative adversarial networks (GANs), significantly improving defect recognition performance in small-sample scenarios. These research results demonstrate the great potential of deep learning in emotional design, but its application in the field of smart health monitoring equipment is still insufficient. In summary, deep learning technology has shown significant advantages in demand analysis, product design generation, and engineering decision support. Existing studies have also demonstrated that data-driven optimization and intelligent decision-making can substantially improve engineering efficiency in manufacturing systems, such as production scheduling and resource allocation [17]. However, most existing research focuses on a single technology or a single design stage, lacking a unified data-driven intelligent product development framework that integrates user requirement acquisition, design generation, and engineering optimization.

Based on the aforementioned research status, this paper proposes a data-driven intelligent product development framework integrating deep learning, Kansei Engineering, and TRIZ theory, aiming to provide end-to-end engineering design support for intelligent health monitoring devices. Grounded in massive amounts of online user data, this framework constructs an AI-assisted product development process encompassing "user needs acquisition—design knowledge mapping—intelligent solution generation—engineering optimization decision-making." First, deep learning technology is used to analyze online reviews and product image data to automatically identify user needs and product features. Second, Kansei Engineering is leveraged to establish a mapping relationship between user needs and product design elements, providing data support for product design decisions. Finally, TRIZ theory is combined to identify and resolve engineering conflicts in the product development process, achieving synergistic optimization of product functionality, user needs, and design innovation. The proposed framework is validated through case studies of smartwatches and smart bracelets. The results show that this framework can effectively improve the efficiency of user needs analysis, support engineering design decisions, and provide a scalable technical path for the data-driven development of intelligent health monitoring devices and other intelligent products.

2. Methods

2.1 Research framework

To support data-driven intelligent product development for wearable smart health monitoring devices and improve the efficiency of user demand identification and engineering design decision-making, this paper proposes a data-driven intelligent product development framework integrating deep learning, Kansei Engineering, and TRIZ theory. The overall process is shown in Fig. 1. Based on massive amounts of online user data, this framework constructs four interconnected product development stages: data acquisition and processing, user demand identification, design knowledge mapping and solution generation, and engineering optimization decision-making. This provides end-to-end engineering design support from user demand acquisition to product solution optimization. The first part is data acquisition and processing. Web crawling technology is used to collect user review data and product image data from e-commerce platforms and social media. Data cleaning, noise reduction, and standardization are performed through text analysis, image classification, and data preprocessing to construct a dataset that supports product development and provides a reliable foundation for subsequent user demand analysis and design decisions. The second part is user demand identification. Deep learning technology is used to analyze user reviews and product images, automatically extracting user demand features and product design features. By combining the semantic differential method (SD) and cluster analysis methods from Kansei Engineering, the framework establishes a mapping relationship between user needs and product design elements, systematically transforming user needs into design knowledge and providing data support for engineering design decisions. The third part is design scheme generation. Using Generative Adversarial Network (GAN) technology, diverse product design schemes are generated from the user-need mapping results, enabling the intelligent generation of product design concepts and providing data-driven support for product innovation. The fourth part is engineering optimization decision-making. TRIZ theory is introduced into the product development process to analyze and optimize engineering conflicts in design schemes, achieving synergistic optimization among product functions, user needs, and design innovation and ultimately forming a product design scheme that meets user needs and provides systematic decision support for the engineering design of intelligent health monitoring equipment.

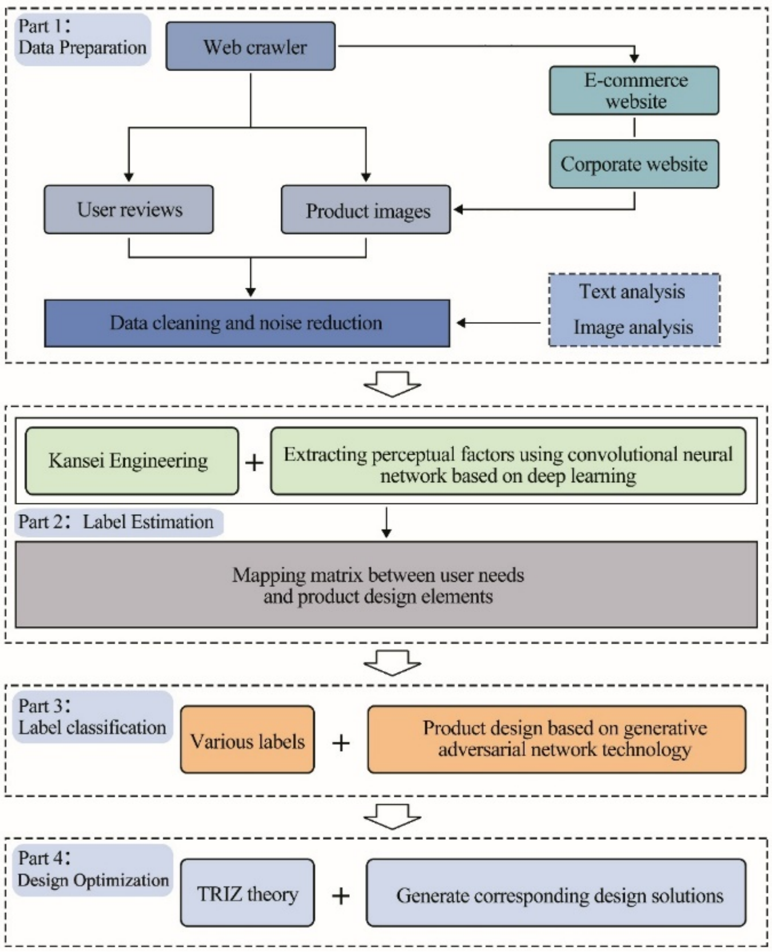

Fig. 1 Data-driven intelligent product development framework for wearable health monitoring devices

2.2 Product data collection and processing technology

With the rapid development of the Internet, social media, mobile terminals, and wireless sensor technology, the amount of data generated and stored worldwide has surged, while artificial intelligence is evolving from supervised toward unsupervised learning.

In traditional Kansei Engineering research, product samples are typically collected manually from printed publications, field investigations, e-commerce platforms, and other sources, after which the images are screened by researchers. This labor-intensive process is time-consuming and susceptible to subjective judgment, and the resulting sample set may not adequately represent the diversity of existing products. With the rapid growth of online product data generated through e-commerce platforms, social media, and other digital channels, manual collection and conventional data-processing methods are increasingly unable to handle the volume, variety, and rate of data generation. Data-driven methods, such as automated web crawling and image screening, can improve the efficiency and consistency of sample collection and convert large-scale product data into structured resources that support subsequent design analysis and decision-making.

Evolving consumer needs are driving innovation in design paradigms: traditional function-oriented products can no longer meet market demands, and a focus on users' emotional experience has become central to differentiated competition. Current research on user requirements focuses on two dimensions: demand acquisition and preference analysis. Traditional manual collection methods, however, suffer from bottlenecks such as low efficiency and information lag. Advances in big data technology are driving a shift toward a data-driven research paradigm, enabling accurate identification of needs through in-depth mining of user behavior data.

Based on the massive volume of online reviews accumulated by e-commerce platforms, this study constructs a systematic research framework from data collection to demand extraction.

First, original review data are collected using web crawlers. After data cleaning and preprocessing, key emotional image words are extracted using natural language processing (NLP) algorithms (Fig. 2). This method overcomes the temporal and spatial limitations of traditional surveys, captures real needs through real-time user feedback, and provides quantitative decision support for product optimization.

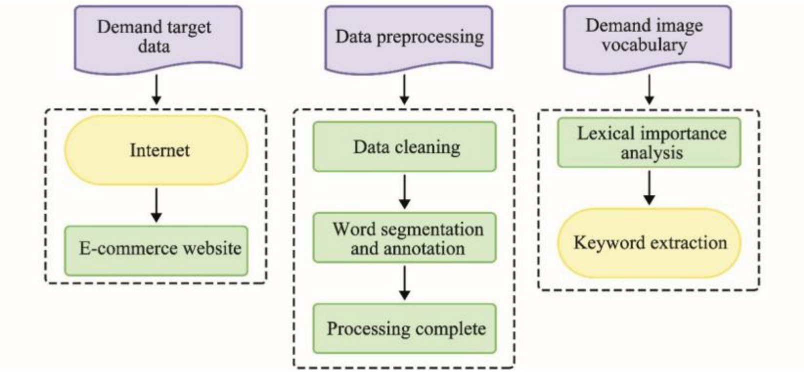

Fig. 2 User demand mining ideas

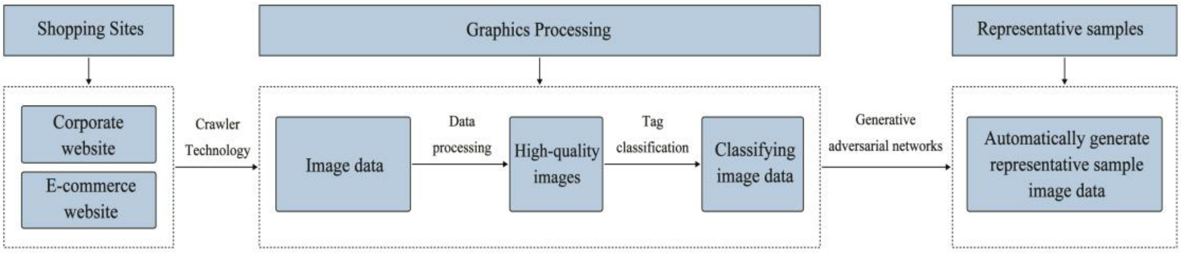

Fig. 3 Product representative sample collection ideas

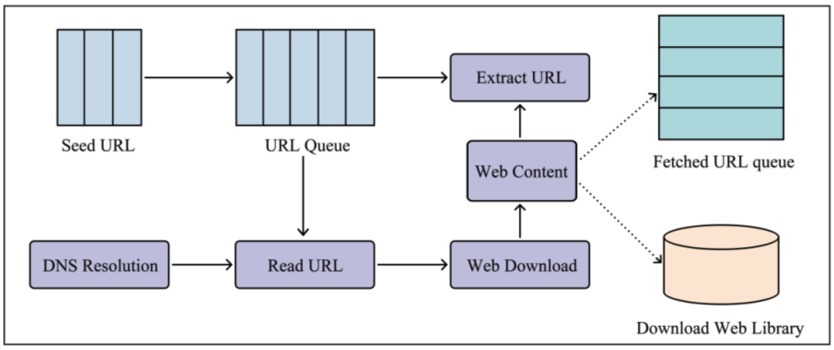

Fig. 4 Flow chart of web crawler

This study used crawler technology to collect a large volume of data on user requirements and feedback related to health monitoring equipment from social media and online user comments. Combined with the questionnaire survey results, these data provide an important basis for understanding the pain points and needs encountered by users in actual use. Compared with traditional laboratory data collection methods, real-world Internet data are more representative and timely and can more accurately reflect users' actual experiences. The collection process is shown in Fig. 3.

To address the problems of time-consuming product image collection and outdated styles, web crawler technology can rapidly obtain large volumes of up-to-date data. Using web crawlers to collect representative product samples can significantly improve both the quantity and quality of the samples. The workflow is shown in Fig. 4.

Web crawlers are programs that automatically collect data from the Internet according to predefined rules. They are highly customizable, low-cost, and easy to operate, so they are widely used in various fields. Because product review page analysis and data extraction require centralized collection of review data for a given product, this study adopts a depth-first strategy to address the lengthy user demand acquisition process and the limited number of demand-related image words.

2.3 Image classification using label learning

For the classification of image data samples, label learning can automatically identify image category features, thereby enabling rapid classification and improving sample acquisition efficiency. In this study, product images have multiple characteristic attributes (material, pattern, color, etc.), each of which can be analyzed further. Therefore, a multi-label learning method based on a deep graph convolutional network (GCN) is used for classification.

First, all characteristic attributes of the product images are analyzed. These features are converted into labels and represented by nodes, while the relationships between nodes are represented by edges. In convolutional neural networks, convolution kernels are used to extract information; similarly, graph convolutional layers use the neighbors of a specific node for convolution operations. If two nodes share an edge, they are neighbors. In graph convolution, the learned weights are multiplied by the features of all neighboring nodes, after which an activation function is applied. The formulation is as follows:

$$h = f\left(\sum_{j\in N}\frac{1}{c_{ij}}h_{vj}w\right) \tag{1}$$

$$A_{\mathrm{norm}} = D^{-\frac{1}{2}}AD^{-\frac{1}{2}} \tag{2}$$

Here, N denotes the set of neighboring nodes of v_i, including v_i when self-loops are used, $h_{v_j}^{l}$ denotes the feature representation of neighboring node v_j at layer l, w^l is a trainable weight matrix shared across neighboring nodes, and f is a nonlinear activation function. The coefficient c_{ij} is the symmetric normalization factor for edge (v_i, v_j), with $c_{ij} = \sqrt{d_i d_j}$, where d_i and d_j are the corresponding node degrees. A is the adjacency matrix after the addition of self-loops, where applicable, D is its diagonal degree matrix, and A_{norm} is the symmetrically normalized adjacency matrix.

Categorizing images with the same labels through machine learning can improve the classification efficiency of product samples, help designers analyze features more effectively, and identify current product design trends.

2.4 Research methods of Kansei Engineering

As user experience is increasingly valued in product design, sensory engineering, as a design method that can capture and reflect user requirements, has gradually become a focus of academic research and practical application. Through sensory engineering, designers can not only more accurately understand users' emotional responses when using products but also integrate users' needs into product design, thereby enhancing product competitiveness. Wang *et al.* [18] explored the impact of smartwatch interface design on user experience and product acceptance from the perspective of specific applications. The study found that smartwatch interface design, as an important aspect of an emerging wearable device, is directly related to user experience. The study indicated that successful smartwatch interface design should conform to users' natural interaction habits to reduce learning costs and enhance product competitiveness by improving user experience. Raptis *et al.* [19] revealed the trade-off between smartwatch functionality and aesthetics through empirical research. The study showed that although functionality is an important factor considered by users, design aesthetics, especially for consumers who value fashion and individuality, often play a decisive role in the final choice.

Kansei Engineering is widely used in product design, offering advantages across applications ranging from new product development to smart-device interface design. Future research can further combine Kansei Engineering with technologies such as artificial intelligence and big data analysis to more effectively capture and reflect users' needs and enhance user experience and market competitiveness. Data mining, as a key technology for analyzing user needs, is important for mapping models and design decision-making. By mining user needs through multiple channels, the richness and reliability of data can be enhanced, providing stronger support for product design.

Research on Kansei Engineering has developed a set of established methodological paradigms, including methods for constructing perceptual demand information spaces and mining demand information. This process is roughly divided into three steps: acquisition and analysis of perceptual needs; analysis of design components; and mapping of perceptual needs. The methods involved in this study include questionnaire surveys, semantic differential analysis (SD), cluster analysis (CA), artificial neural network methods, and the Human Interface Elements (HIEs)

2.5 Deep learning technology

In recent years, the rapid development of the Internet, social media, mobile terminals, and wireless sensor technology has led to a surge in global data generation and storage, while artificial intelligence is evolving from supervised toward unsupervised learning. Artificial intelligence systems continue to improve by learning and discovering patterns from massive datasets across various industries. Rich training datasets provide further opportunities for their application across industries.

Generative design has become an important application of deep learning in product design. Through deep generative models, designers can rapidly generate diverse and innovative design solutions. Wang *et al.* [20] reviewed big data analytics technologies for intelligent manufacturing systems, noting that manufacturing intelligence is increasingly evolving from traditional model-driven approaches to data-driven ones. Their review indicates that big data analytics supports decision-making across various stages, such as product design, production planning and scheduling, process and quality control, and prognostics and health management, while also providing a pathway for generative design. Zhang *et al.* [21] proposed a clean production (CP) approach that combines product lifecycle management (PLM) with big data analysis (BDA), aiming to address knowledge shortages in the manufacturing process and promote successful implementation of CP strategies through data mining and knowledge discovery. In addition, Liao *et al.* [22] proposed a Semantic-Spatial Aware GAN (SSA-GAN) model for text-to-image synthesis. By introducing Semantic-Spatial Aware (SSA) blocks, the model enables effective and deep integration of text and image features, improving the consistency and detailed representation of generated images and text descriptions.

The application of deep learning technology in design automation has greatly improved the efficiency and accuracy of product design. Sun [23] explored the potential of automated icon generation using generative adversarial networks (GANs), proposed a multi-feature icon generation network (MFlGN) based on conditional classification GANs, and achieved better design quality and diversity on icon datasets than existing methods by introducing a multi-feature recognition module.

This study applies label learning and GANs to product sample collection and improves sample representativeness and collection efficiency through deep learning. GANs are used to fuse different product image features, providing a new deconstruction method. The collection process comprises entering keywords to obtain e-commerce images, preprocessing the data, analyzing features, automatically annotating and classifying images, and using GANs to fuse features and generate representative images. Designers then build a feature library to improve the accuracy of the user demand model.

2.6 Representative samples of products generated by adversarial networks

In the early stages of traditional research, designers usually collected product images manually from books, newspapers, and the Internet and screened representative images as samples. This manual collection method cannot cover most product samples and makes it difficult to accurately capture current trends. This study automatically obtains product images through web crawlers. This method can collect more samples and overcome the low efficiency and insufficient sample representativeness of traditional manual screening.

To further optimize the sample library, this study introduces generative adversarial network (GAN) technology for feature-fusion learning, thereby generating a smaller set of new images similar to those in the sample library and compressing the sample library. Feng *et al.* [24] discussed a method for automatically generating ICD-11 codes based on deep learning. This method maps the natural-language text of electronic medical records to ICD-11 codes through modeling, significantly improving coding efficiency and accuracy. Ivanescu *et al.* [25] proposed a method for automatically determining deep neural network architectures using the evolutionary computing paradigm and optimizing deep learning models through evolutionary algorithms. A generative adversarial network (GAN) based on a deep convolutional neural network is proposed in [26]. A GAN includes a generative model and a discriminative model. Through adversarial training between the two models, highly realistic image data can be generated. Compared with the variational autoencoder (VAE) framework, GAN training is more complex, but it can better capture features when processing large datasets, and the generated images are more interpretable and perform better.

Current image-to-image translation methods based on generative adversarial networks mainly include Pix2Pix, CycleGAN, and StarGAN. This study uses StarGAN to extract multi-label image features and perform feature-fusion learning. The structures of its generator and discriminator are shown in Fig. 5.

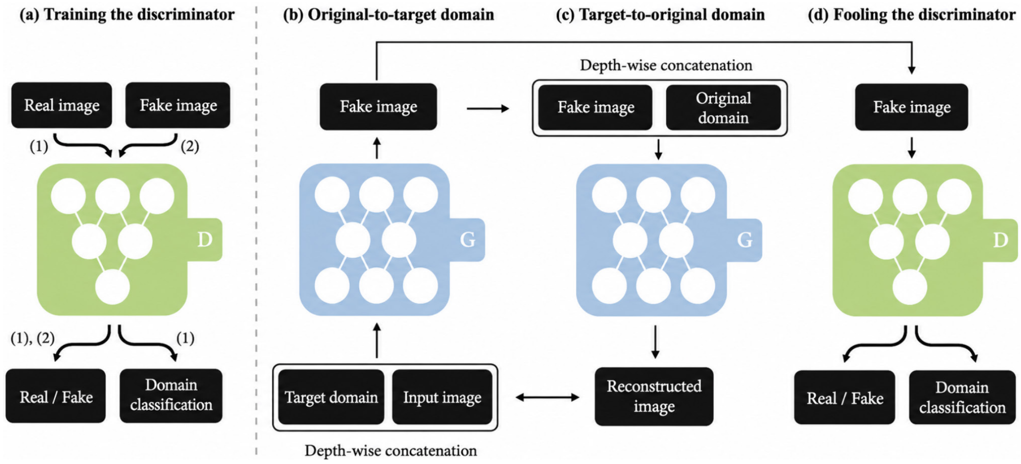

Fig. 5 Schematic diagram of the StarGAN model structure

2.7 Definition and resolution principles of technical conflicts in TRIZ theory

TRIZ theory, proposed by Altshuller, is a method for solving inventive problems by analyzing design contradictions and conflicts. It is particularly useful in the problem-definition and solution stages and is characterized by a scientific, rigorous, and logical approach to innovation [27, 28]. In the design of wearable smart health monitoring equipment, technical and physical conflicts can hinder optimization. This study integrates TRIZ theory with Kansei Engineering demand analysis to systematically analyze key contradictions and propose innovative solutions.

A technical conflict arises when improving one aspect of a system negatively affects another. By analyzing patents worldwide, TRIZ researchers identified a limited set of reusable principles applicable across fields. Altshuller's 40 inventive principles, based on engineering principles, are widely applicable. Physical conflicts involve irreconcilable contradictions in product design, such as balancing equipment lightness with durability. Using TRIZ physical contradiction analysis, this study proposes high-strength lightweight materials or double-layer structures. Specifically, the "physical separation principle" and "reverse principle" are combined, using different materials in different parts to enhance durability without adding weight.

3. Empirical study

3.1 Image and comment data preparation

This paper uses smartwatches as a case study. First, web crawler tools were used to collect product images of smartwatches and smart bracelets through Google Search and to retrieve related images and comments from platforms such as Amazon, JD.com, and Taobao. Second, all product images were manually checked, and unnecessary images were removed. Finally, 16,157 watch images and 13,476 bracelet images were collected, together with a total of 12,503 comments containing partial review text.

3.2 Label learning and image classification

After analyzing the morphological features of the collected product images, relatively simple morphological features that could be extracted using deep learning were selected, and multi-label annotation was performed based on these features to establish a mapping relationship between images and labels, as shown in Fig. 6.

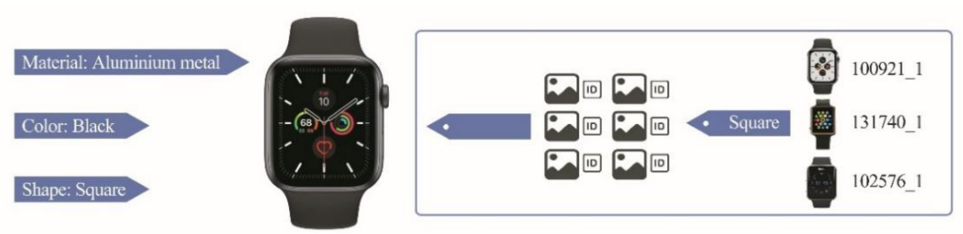

Fig. 6 Data augmentation process

Next, the 2,517 processed images were augmented to increase the number of training samples, alleviate insufficient model learning caused by limited training data, and improve model robustness. This study used rotation and mirroring transformations for data augmentation. Rotation included rotating images by 90°, 180°, and 270°, while mirroring involved reflecting the left and right or upper and lower parts of an image about its vertical or horizontal axis. Through these processes, the dataset was expanded sixfold, yielding 15,102 high-quality training samples.

Finally, a generative adversarial network training experiment was conducted using the smartwatch image samples. The processed experimental sample data are shown in Table 1.

During training, front-view smartwatch image data were input into deep convolutional generative adversarial network (DCGAN), StarGAN, etc. to generate new images based on the classified product images. The learning rate was set to 0.00005, the Adam optimizer was used for optimization, the batch size was 100, and the number of training rounds was 100. Changes in the loss values of the network discriminator and generator are shown in Fig. 7.

Table 1 Sample distribution of the generative adversarial network dataset

Tag	Tag type	Sample count
Dial outline	Square	2650
	Rectangle	4862
	Round	3986
	Oval	3604
Have color or not	Color	5681
	No color	9421
Overall material	Plastic	6089
	Metallic	9013

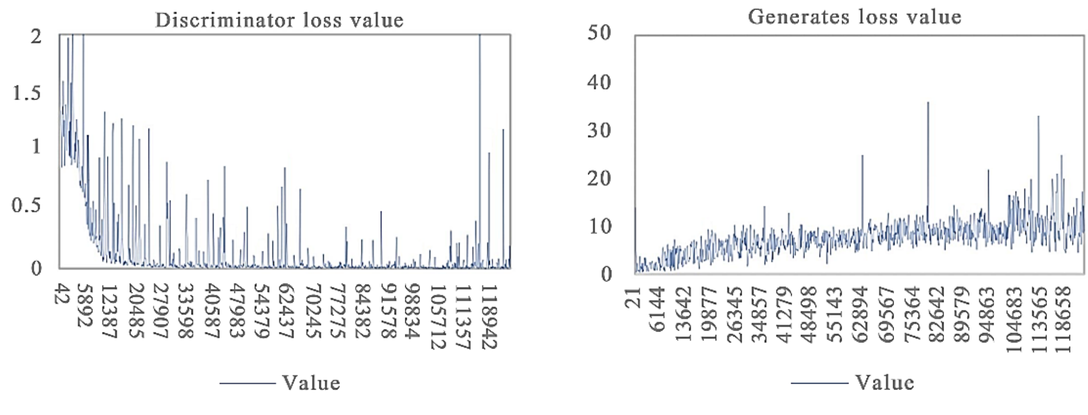

Fig. 7 Loss values during generative adversarial network training

The training loss curves show that the discriminator loss gradually decreases, while the generator loss tends to stabilize. Overall, the training process of this generative adversarial network exhibits substantial fluctuations. The generated output images indicate that, through training with the two generation algorithms, the generative network can learn the statistical distribution and morphological features of existing smartwatch images and generate representative new images based on the learned distribution. Some generation results are shown in Fig. 8. However, some erroneous outputs remain and require manual screening to prevent them from entering the next stage of the generation process.

Fig. 8 GAN generation results

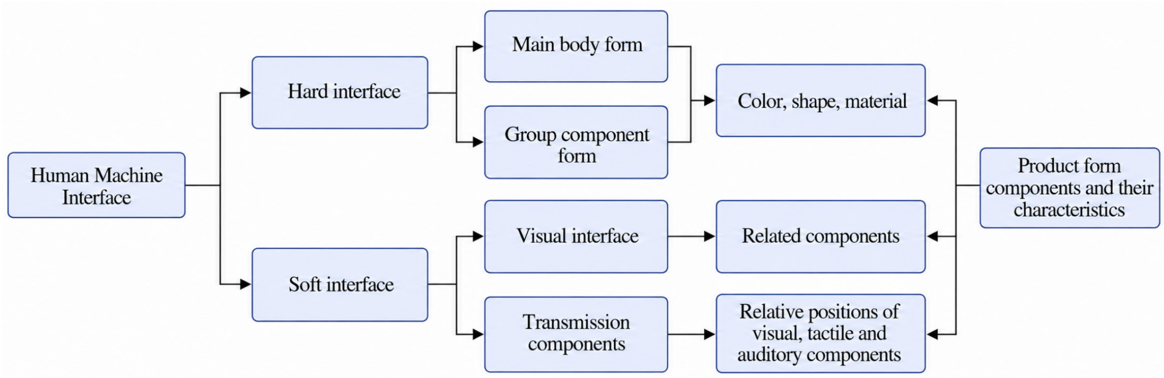

Fig. 9 Analysis process for morphological characteristics

The generative network is used to learn the statistical distribution and morphological features of existing smartwatch images, and representative new images are generated based on the learned distribution. The experimental results show a certain degree of diversity. In the generated square-dial samples, the colors and materials vary, and the generated dial-outline styles also show diversity under the color and material labels. This phenomenon is closely related to the sample data distribution of a given label, but the overall results remain informative. Designers can intuitively identify the required product features from these sample images and further analyze the sample features generated by each label, as shown in Fig. 9.

The hard-interface morphological characteristics of the product are first analyzed from two aspects: the main-body morphology and the component morphology. The deconstruction results are detailed in Table 2.

Table 2 Catalog of product form components and their characteristics

Interface type	Component category	Product-form feature	Characteristics
Hard interface	Main part	A1 Main body shape	Round (1), Square (2), Oval (3)
		A2 Main body material	Metal (1), Plastic (2), Composite materials (3)
		A3 Main body color	Single color (1), Multiple colors (2)
		A4 Main body width	Wide (1), Narrow (2)
	Group components	B1 Watch buckle material	Stainless steel (1), Titanium (2), Plastic (3)
		B2 Watch strap texture	Strong (1), Weak (2)
		B3 Watch bezel material	Silicone (1), Metal (2)
		B4 Watch strap material	Leather (1), Stainless steel (2), Nylon (3), Silicone (4)
Soft interface	Information components	C1 Speaker position	Side (1), Bottom (2)
		C2 Power button location	Right (1), Left (2)
		C3 Display size	Less than 1 inch (1), 1-1.5 inches (2), 1.6-2 inches (3), 2 inches or more (4)
	Feedback	D1 Gravity sensor	Keen (1), General (2)
		D2 Screen color temperature	Warm colors (1), Natural light (2), Cool colors (3)
		D3 Icon recognition accuracy	Difficult (1), Easy (2), Average (3)

3.3 Emotional preference recognition

First, the obtained text data are further processed to remove irrelevant information, and a stop-word list is applied to clean and filter the text. Irrelevant information can be broadly divided into the following categories:

- Because web crawlers obtain data from web pages, the collected text data may contain redundant text;
- The comment text may contain many punctuation marks, irrelevant numbers, and letters;
- The dataset may contain duplicate comments.

The key adjectives and their weight parameters in the comments are extracted using the TextRank algorithm. TextRank is a graph-based ranking algorithm for keyword extraction and document summarization. It is derived from Google's PageRank algorithm for ranking the importance of web pages. It uses co-occurrence information (semantics) between words in a document to extract keywords. It can identify keywords and keyword groups from a given text and use extractive summarization to identify key sentences.

The basic idea of the TextRank algorithm is to represent a document as a network of words, with links in the network representing semantic relationships between words. The TextRank calculation is given by:

$$WS(V_i) = (1-d) + d * \sum_{V_j \in In(V_i)} \frac{W_{ji}}{\sum_{V_k \in Out(V_j)} W_{jk}} WS(V_j) \tag{3}$$

Here, $WS(V_i)$ denotes the TextRank score of candidate word (vertex) V_i, $In(V_i)$ denotes the set of vertices with edges directed to V_i, $Out(V_j)$ denotes the set of vertices reachable from V_i, W_{ji} is the weight of the co-occurrence edge from V_j to V_i within the selected text window, and d is the damping factor set to 0.85. The scores are updated iteratively until convergence [29].

The importance of the adjectives is then analyzed using the TextRank algorithm to obtain the corresponding demand keywords and their weight parameters. The top 30 adjectives are listed in Table 3.

Table 3 Demand keywords and their weights

Demand keywords	Weight	Demand keywords	Weight
Delicate	0.8568	High-tech	0.0574
Generous	0.7589	Personalized	0.5374
Responsive	0.3562	Smooth	0.3481
Fashionable	0.2125	Lightweight	0.2459
High-end	0.4254	Convenient	0.2571
Minimalist	0.5014	Cost-effective	0.3658
Elegant	0.7561	Colorful	0.5726
Comfortable	0.1568	Classic	0.4814
Durable	0.2354	Innovative	1.2788
Intelligent	0.3564	Multi-functional	4.3751
User-friendly	0.9351	Thoughtful	1.8452
Dazzling	0.0258	Professional	0.3647
Practical	0.3587	Steady	0.2541
Precise	0.2575	Dynamic	1.2748
Aesthetically pleasing	0.8534	Business	3.2156

Finally, the above adjectives were scored for similarity on a 1–5 scale, with higher scores indicating greater similarity in meaning, and a 30 × 30 similarity matrix was constructed. The matrix was then imported into MATLAB for K-means cluster analysis. The results are shown in Table 4.

By clustering the top 30 demand adjectives, three representative demand adjectives were obtained: “high-end”, “delicate”, and “dazzling”.

Table 4 Clustering results

Group 1	Distance	Group 2	Distance	Group 3	Distance
High-end	3.264	Delicate	3.127	Dazzling	2.867
Thoughtful	3.326	Generous	3.426	Durable	2.948
Minimalist	3.425	Comfortable	3.537	Intelligent	3.247
Convenient	3.957	Elegant	3.846	User-friendly	3.542
Dynamic	4.026	Cost-effective	4.238	Responsive	3.757
Colorful	4.251	Steady	4.531	Practical	4.268
Classic	4.368	Fashionable	4.687	Precise	4.587
Lightweight	4.527	-	-	High-tech	4.784
Smooth	4.632	-	-	Personalized	4.879
Aesthetically pleasing	4.826	-	-	Multi-functional	4.978
Professional	4.921	-	-	Innovative	5.016
-	-	-	-	Business	5.124

3.4 Construction of user requirements model

To explore the diversity and preference characteristics of user needs and build a universal demand mapping model, this study proposes a method for constructing a user demand mapping model. Based on Kansei Engineering, this method combines product feature components with users' perceived needs using a cluster analysis algorithm to derive an optimized solution that can guide product design practice. The construction logic of the user demand mapping model is shown in Fig. 10.

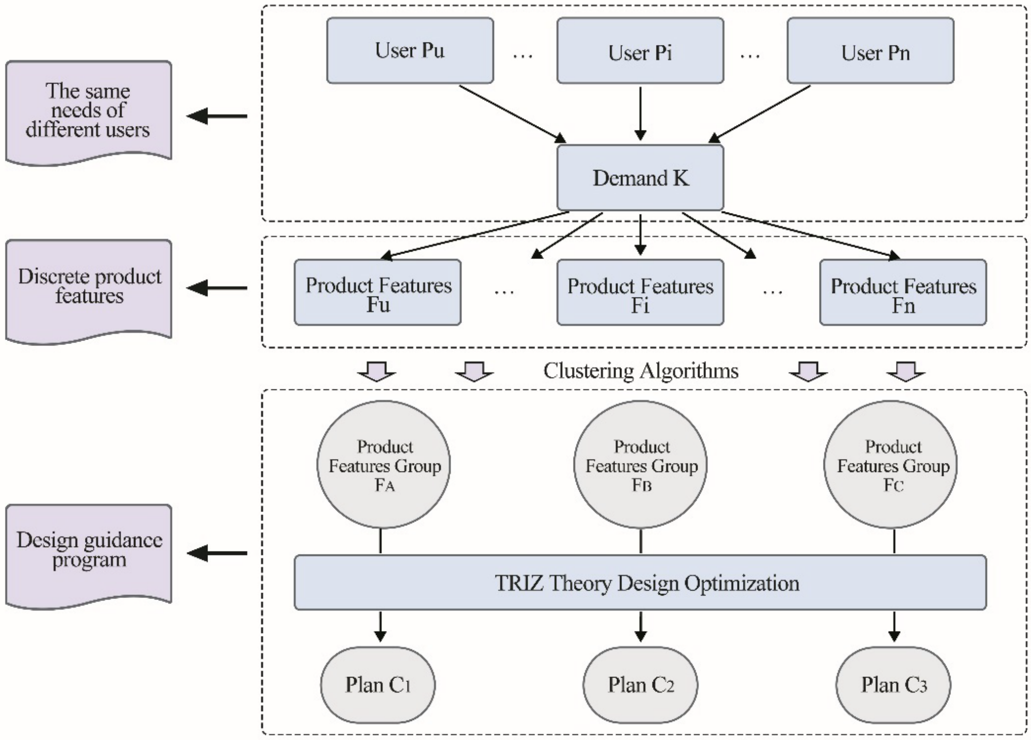

Fig. 10 User demand mapping model construction ideas

The user demand mapping model proposed in this study can analyze the product-feature preferences shown by different users for the same demand. Its core description can be summarized as follows:

- For users P_u, P_i, and P_n, all three share the same demand K for a given product.
- Any product can be decomposed into n product features F_n, which typically cover key elements such as product shape, material, and color. Reasonable and comprehensive deconstruction of product features is crucial for building a high-quality demand mapping model because it enables more accurate exploration of users' underlying requirements.
- Using clustering algorithms, the similarity of the emotional preferences of multiple users for product features F_u, F_i, and F_n under the same demand can be calculated. Based on this,

similar preferences across multiple user types are reorganized into product-feature combinations such as F_A, F_B, and F_C. Each solution group C represents the demand preferences or similar preferences of a particular user type P. The design guidance solution composed of these carefully combined product features can broadly cover and accurately address the similar needs of most users for a given product.

3.5 Construction of cognitive space of analytical elements based on user needs

This study constructs a user demand cognitive space based on user cognition. Constructing a mapping model between this space and product form requires a user demand cognitive experiment. By parameterizing these qualitative data, the user demand cognitive space can be constructed. First, K-means cluster analysis is used to consolidate the demand space, and the product form components and their characteristics are quantitatively preprocessed. This process uses Hayashi's Quantification Theory Type I. Assume that there are X types of form components, and each type can be encoded as $\{X_1, X_2, X_3, \dots, X_n\}$. The features under each type of form component can be assigned values from 1 to n. For example, the features of the k-th type of form component can be expressed as $\{X_{k1}, X_{k2}, X_{k3}, \dots, X_{kj}\}$, where j represents the total number of features under the k-th type of form component.

Similarly, the features X of all types of morphological components can be quantified, providing the data foundation for subsequent quantitative analysis. Because each user response has only two states, "selected" and "unselected", corresponding to values 1 and 0, respectively, we can calculate the perceived parameter value i for feature m of morphological component k under the demand. When the feature is selected by the user, its normalized value is 1; otherwise, it is 0. Finally, when all n users have selected the features of all r types of morphological components k under demand X, these normalized data are entered into matrix X to form the parameterized matrix X_k, as follows:

$$X_k = \begin{matrix} X_{a1}^1\{k\} & X_{a2}^2\{k\} & & X_{at}^i\{k\} & X_{ar}^n\{k\} \\ X_{b1}^1\{k\} & X_{b2}^2\{k\} & \cdots & X_{bt}^i\{k\} & X_{br}^n\{k\} \\ \vdots & \vdots & & \vdots & \vdots \\ X_{m1}^1\{k\} & X_{m2}^2\{k\} & \cdots & X_{mt}^i\{k\} & X_{mr}^n\{k\} \\ \vdots & \vdots & & \vdots & \vdots \\ X_{n1}^1\{k\} & X_{n2}^1\{k\} & \cdots & X_{nt}^i\{k\} & X_{nr}^n\{k\} \end{matrix} \tag{4}$$

This study used a clustering algorithm to construct a mapping model between user needs and product form components. Specifically, the k-means clustering method was used to cluster product form components. First, the component features were classified into k categories, and then n component features were assigned to these categories. Using Euclidean distance as the measure, highly similar component features were clustered together while maintaining separation between categories. The formulation is:

$$L_i = \arg\min \parallel X_i - \mu_j|; (1 \leq j \leq k) \tag{5}$$

Here, L_i is the category closest to the cluster center, X_i is the object sample, and μ_j is the cluster center.

To build a mapping model between user needs and product features, this study conducted a questionnaire survey. The experiment used “high-end”, “delicate”, and “dazzling” as the target needs and selected 42 functional catalogs as experimental samples. A total of 29 valid questionnaires were collected. By parameterizing these qualitative variables in Microsoft Excel, the input matrix for each participant across all feature catalogs was obtained.

3.6 Construction and evaluation of a mapping model between user needs and product form components

The parameterized demand preference matrix was imported into MATLAB for cluster analysis. Candidate numbers of groups were set to 2, 3, and 4, and their suitability was evaluated. Three groups were ultimately selected. The clustering results were output and used to build a user demand mapping model, as shown in Table 5. The product features in the three solution groups were evenly distributed, and the clustering results were satisfactory. Table 5 lists the average and deviation values of the features under each solution, reflecting the degree of divergence. Feature representativeness is strong when the deviation value is close to zero. The user demand mapping model was analyzed to obtain the key feature combinations that meet the demand preferences, as shown in Table 6.

Table 5 User requirement mapping model

Product features	Category 1			Category 2			Category 3		
	37.6 %			21.4 %			41.0 %		
	Number	Mean value	Deviation	Number	Mean value	Deviation	Number	Mean value	Deviation
A1 Main body shape	(1)	0.700	0.482	(2)	1.000	0.000	(1)	0.500	0.549
A2 Main body material	(1)	0.500	0.523	(2)	0.800	0.448	(2)	0.800	0.405
A3 Main body color	(2)	0.600	0.517	(1)	0.600	0.550	(2)	0.700	0.517
A4 Main body width	(2)	0.900	0.315	(1)	0.800	0.448	(2)	0.500	0.549
B1 Watch buckle material	(3)	0.800	0.426	(2)	0.600	0.549	(2)	0.700	0.517
B2 Watch strap texture	(2)	0.600	0.514	(1)	1.000	0.000	(1)	0.700	0.517
B3 Watch bezel material	(1)	0.900	0.315	(2)	0.800	0.448	(2)	1.000	0.000
B4 Watch strap material	(3)	0.600	0.517	(1)	0.800	0.448	(2)	0.800	0.405
C1 Speaker position	(2)	0.600	0.517	(1)	1.000	0.000	(1)	0.500	0.549
C2 Power button location	(2)	0.800	0.426	(2)	0.600	0.549	(1)	0.700	0.517
C3 Display size	(2)	0.400	0.517	(1)	0.600	0.549	(2)	0.500	0.549
D1 Gravity sensor	(1)	0.500	0.523	(1)	1.000	0.000	(2)	1.000	0.000
D2 Screen color temperature	(2)	0.700	0.482	(1)	0.400	0.550	(3)	0.700	0.517
D3 Icon recognition accuracy	(2)	0.600	0.517	(3)	0.800	0.448	(2)	0.700	0.517

Table 6 Key product feature combination plans

Combination plan 1	Combination plan 2	Combination plan 3
The main body shape is round	The main body shape is square	The main body shape is round
Main body material is metal	Main body material is plastic	Main body material is plastic
Main body color is multiple colors	Main body color is single color	Main body color is multiple colors
Main body width is narrow	Main body width is wide	Main body width is narrow
Watch buckle material is plastic	Watch buckle material is titanium	Watch buckle material is titanium
Watch strap texture is weak	Watch strap texture is strong	Watch strap texture is strong
Watch bezel material is silicone	Watch bezel material is metal	Watch bezel material is metal
Watch strap material is nylon	Watch strap material is leather	Watch strap material is stainless steel
The speaker is located the bottom of the main body	The speaker is located on the side of the main body	The speaker is located on the side of the main body
The power button is located on the left side of the main body	The power button is located on the left side of the main body	The power button is located on the right side of the main body
Display size is 1.6-2 inches	Display size is less than 1 inch	Display size is 1.6-2 inches
Gravity sensor is keen	Gravity sensor is keen	Gravity sensor is general
The screen displays a color temperature of natural light	The screen displays a warm color temperature	The screen displays a cold color temperature
Icon recognition accuracy is easy	Icon recognition accuracy is average	Icon recognition accuracy is easy

Based on these product-feature combination schemes, the product demand preferences of different user types can be rapidly inferred, providing designers with a basis for developing products that better meet user requirements.

3.7 Resolving conflicts between requirements and design elements

To improve product innovation capability, this paper analyzes wearable intelligent health monitoring equipment using TRIZ theory. TRIZ principles are applied to address technical and physical conflicts through a contradiction matrix. Three groups of conflicts are identified and transformed into TRIZ problem models, as shown in Table 7.

Table 7 TRIZ problem models for three combination plans

Combination number	Conflict type	Negative correlation characteristics	General engineering parameters
Combination plan 1	Physical conflict: metal body vs. nylon strap	Heavy metal body; Nylon strap is lighter	1. Weight of moving object
	Technical conflict: natural-light temperature vs. icon recognition	Natural-light temperature reduces the contrast of icons; Icon recognition is difficult	18. Illumination intensity; 24. Information loss
Combination plan 2	Technical conflict: plastic body vs. leather strap	Plastic body looks low-end; Leather strap looks high-end	12. Shape; 27. Reliability
	Technical conflict: warm color temperature vs. icon recognition	Warm color temperature reduces icon clarity; Affects recognition accuracy and efficiency	18. Illumination intensity; 28. Test Accuracy
Combination plan 3	Physical conflict: plastic body vs. stainless steel band	The low-end feel of the plastic body; The premium feel of a stainless steel strap	12. Shape; 27. Reliability
	Physical conflict: cool color temperature vs. icon recognition	Cold-color temperature makes the screen glare; Affects the comfort of use	34. Adaptability or versatility

The conflicting problems can be solved one by one using TRIZ inventive principles::

- Innovation principle 1: Segmentation. Design the body with partial metal sections or hollow structures to reduce the weight of the metal part and match the lightweight nylon strap. Innovation principle 32: Changing Color. Use icon colors with stronger contrast to ensure that icons can be easily identified even under a natural-light color temperature, improving user experience.
- Innovation principle 5: Merging. Through surface treatment or coating, the plastic body is given a more upscale appearance that is consistent with the texture of the leather strap and enhances the overall appearance. Innovation principle 15: Dynamicity. Add automatic brightness and color-temperature adjustment functions to the screen to maintain appropriate icon clarity and recognition under different lighting conditions.
- Innovation principle 35: Change of physical and chemical parameters. Use special coatings or embed metal elements in the plastic body to enhance the overall upscale appearance of the watch and maintain consistency with the premium texture of the stainless steel strap. Innovation principle 3: Local quality. Locally adjust the screen brightness to meet the brightness requirements of cool colors and different environments, reduce glare, and ensure comfort during long-term use.

By applying these TRIZ inventive principles, potential technical conflicts in the design can be systematically resolved, improving overall device performance and user experience.

3.8 Product design plan

Through the above design analysis, the product-form combination plans are obtained. Design sketches are then developed based on main-body width, material, and other attributes, as shown in Fig. 11.

Fig. 11 Design sketches

In the first scheme, the watch has a round metal body in a variety of bright colors, a plastic buckle, and a nylon strap with a slightly weaker texture. The bezel is made of silicone, with the display screen set within it. The display size is between 1.6 and 2 inches, with a natural-light color temperature. The speaker is located at the bottom of the main body, while the power button is located on the left side. The design focuses on functionality and comfort, and the icons are clear and easy to recognize. Using the segmentation principle of TRIZ theory, the partially hollow metal body reduces the weight of the watch, complementing the lightweight nylon strap and emphasizing a high-end appearance.

In Scheme 2, the watch body is square, the main body uses a single color and is made of plastic, the strap is made of strongly textured leather, and the bezel is metal. This design addresses the conflict between the low-end appearance of plastic and high-end leather through the combination segmentation principle in TRIZ theory. The display size is less than 1 inch, and the screen color temperature is warm, creating a warm user experience. The speaker and power button are both located on the side of the watch. The interface design is relatively rich and refined.

In Scheme 3, the watch body is round, made of plastic, available in various colors, and of moderate width, and it is paired with a titanium buckle and a stainless steel strap. The speaker and the power button are located on the right side of the main body. The screen size is 1.6–2 inches, and the display color temperature is cool, which is consistent with the dazzling design concept. The watch is of moderate weight, and the layered design improves wearing comfort.

4. Discussion

The proposed data-driven framework demonstrates the feasibility of integrating deep learning, Kansei Engineering, and TRIZ into a unified process for wearable device development. Unlike conventional approaches relying on designers' experience, it enables automatic user requirement acquisition from large-scale online data, establishes systematic knowledge mappings, generates intelligent concepts, and provides structured optimization. Consequently, it improves the efficiency, consistency, and traceability of engineering design decisions. Compared with traditional user-centered methods, this framework offers distinct advantages: web crawling ensures continuous, large-scale data collection, reducing reliance on manual surveys; deep learning provides intelligent, efficient support for requirement identification and concept generation; and the integration of Kansei Engineering and TRIZ structures the complete workflow from user feedback to engineering optimization. Nevertheless, limitations exist. The framework's performance depends on dataset quality, and TRIZ application still requires domain knowledge. Furthermore, its generalizability requires validation across other product categories beyond health monitoring devices. Future research will focus on three aspects: incorporating multimodal user data (e.g., physiological signals) to improve requirement identification robustness; leveraging advanced AI such as large language models to enhance decision support; and conducting industrial case studies to verify its real-world applicability and generalizability.

5. Conclusion

This study proposed a data-driven intelligent product development framework for wearable health monitoring devices, integrating deep learning, Kansei Engineering, and TRIZ theory into a unified, AI-assisted engineering workflow. This workflow covers online data acquisition, requirement identification, design knowledge mapping, concept generation, and engineering optimization.

Compared with conventional experience-driven approaches, the framework enhances user requirement acquisition through large-scale online data mining. By merging deep learning with Kansei Engineering and TRIZ, it bridges the gap between requirement analysis and engineering design support. A case study validated that the framework effectively automates requirement extraction, concept generation, and systematic optimization, providing a structured, transferable methodology for various intelligent products.

However, limitations remain regarding its reliance on large-scale, high-quality user data and the need for better automated data preprocessing. Future research will focus on overcoming these by exploring the integration of multimodal AI, large language models, the Internet of Things, and digital twin technologies. These advancements aim to improve engineering decision support and promote comprehensive data-driven intelligent product development across broader industrial application scenarios.

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