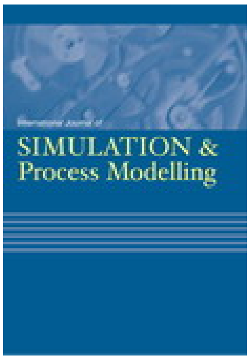

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Generative adversarial networks for simulating emotional resonance in industrial product design

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Abstract: This paper addresses the lack of emotion-oriented simulation in industrial product design by proposing a novel generative adversarial network framework integrated with a quantifiable emotional model. The core of this approach is an emotion-attention mechanism that dynamically guides the form evolution process. Emotional features are first extracted from e-commerce reviews and modelled via an improved support vector regression algorithm to establish a quantifiable mapping between design elements and user emotions. This emotional model is then integrated into a GAN through a multi-head component attention module, which simulates product form evolution by explicitly weighting the contribution of each component to the target emotional resonance. Experimental results demonstrate the effectiveness of this simulation, with the Fréchet inception distance reduced by at least 38.06%, enabling the generation of industrial products that accurately align with user emotional needs.

Keywords: product form simulation; process modelling; emotional resonance; generative adversarial networks; GAN; support vector regression; SVR.

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1 Introduction

In the field of industrial product design, the traditional process heavily relies on designers' experience and intuition, making it difficult to systematically integrate and verify users' emotional needs (Norman, 2004). This often leads to long design iteration cycles and inaccurate predictions of user satisfaction. With the deepening of the experience economy, converting the key but ambiguous factor of user emotions into simulatable and optimisable design parameters has become the core challenge in the intelligent transformation of industrial design. Simulation and process modelling technologies provide a powerful framework to address this challenge (Stafford et al., 2025). They allow researchers to build dynamic mapping models of user emotions – design elements in a virtual environment and systematically simulate the emotional output results under different design decisions, thereby achieving a data-driven closed loop of emotionalised design (Buker et al., 2023).

In recent years, generative artificial intelligence (AI) methods such as generative adversarial networks (GANs) have demonstrated remarkable capabilities in generating creative content, providing new tools for the automated generation of product forms (Kusiak, 2020). However, most existing research treats GANs as a general image generator, and its application has three key limitations that hinder its application in rigorous industrial design simulation processes (Hughes et al., 2021). Firstly, the emotional quantification modelling is weak. Most studies lack a front-end emotional quantification model, which cannot convert unstructured user emotions (such as comments) into precise and structured inputs that can drive the generation process. Secondly, there is a disconnection between emotions and the generation process (Yu et al., 2025). Emotional features are often input as static labels rather than dynamic and interpretable process variables, resulting in a lack of transparency and controllability in the generation process, making it difficult to simulate the path of form evolving according to emotional goals. Thirdly, there is a lack of a systematic simulation perspective (Wu et al., 2025). Existing work focuses on the visual quality of the final generated images, ignoring the integration of emotional analysis-mapping modelling-morphology generation into a computable and iterative simulation process, thus unable to provide comprehensive analytical support for design decisions.

To fill the aforementioned research gap, this paper proposes a GAN-driven modelling method for the evolution of industrial product emotional forms. The objectives include three aspects: constructing a user emotional space model to quantify the distribution characteristics of demands, establishing a design element – emotional correlation mapping model to capture nonlinear relationships, and developing a multi-head attention mechanism to achieve dynamic simulation of emotional weight distribution. Compared with traditional methods, the innovation of this process is reflected in three dimensions: constructing an emotional space through e-commerce platform evaluation data to achieve demand quantification, using an improved support vector regression (SVR) algorithm to establish an interpretable correlation mapping, and utilising the GAN global emotional extractor to achieve precise control of the form evolution.

For the goal of exploring the application methods of Kansei Engineering theory in specific product design, researchers have made important contributions. Traditional industrial product design methods are typically confined to their own specialised fields, with relatively limited communication and collaboration between designers and professionals from other disciplines, resulting in significant professional barriers. This makes it difficult for designers to comprehend and apply knowledge and technologies from other fields during cross-disciplinary integration and innovation, thereby limiting the potential for innovation. Liu et al. (2023) discussed concepts related to emotional imagery in industrial product design and conducted an in-depth analysis of their practical applications within the field of industrial design. Alaniz and Biazzo (2019) pointed out that future design directions will gradually shift toward emotionalisation, and by studying the interrelationships between emotions and product elements, they proposed emotion-driven product design concepts. Chen (2024) systematically analysed consumer emotional reactions using questionnaire experiments and a support vector machine (SVM) classification model, identified key form characteristics of products, and finally validated the effectiveness of the method through case studies. Chao et al. (2023) achieved automatic generation of mood boards and established connections between designers and user needs, applying real data to industrial product design and verifying the feasibility of their approach. The aforementioned methods help identify which product features are most closely related to consumers' emotional experiences, thereby providing quantitative evidence for product design.

During the inspiration phase, AI technology can analyse large amounts of data and information to help designers draw inspiration, discover trends, and explore new creative directions. It can provide insights into market trends and user needs through methods such as data mining and text analysis, thus inspiring new design concepts. The core of experience-driven design relies on the designer's subjective judgment, with no quantifiable standards for understanding user needs or selecting design elements, making it prone to mismatchedc requirements. Traditional machine learning methods, however, employ end-to-end quantitative modelling to convert user needs, design elements, and matching outcomes into computable numerical metrics. Design decisions are grounded in objective patterns extracted through data mining – not personal aesthetics or intuition. This approach precisely captures core user needs and even identifies niche latent demands (such as differentiated emotional needs across user segments). It fundamentally enhances the accuracy of aligning product design with user requirements, preventing scenarios where designers deem a solution excellent while users reject it. Yang (2019) used text mining techniques and self-oganising maps (SOM) to extract users' emotional needs from online reviews and demonstrated the effectiveness of this method using a recliner product on the Amazon shopping platform as an example. Gao and Huang (2022) proposed an emotion-mining approach based on user emotions and machine learning. By applying four machine learning algorithms, including SVM, classification and regression tree (CART), multi-layer perceptrons (MLP), they extracted and measured users' emotional feedback to products from online customer reviews, overcoming the time costs and data scale limitations of traditional questionnaires. Sun et al. (2023) combined fuzzy logic methods with conceptual design; this approach's effectiveness was verified in the conceptual design of wheelchairs.

In the generative design phase of industrial products, data-driven generative product design has become an increasingly popular research topic in academia. Traditional design relies on designers' experience, resulting in lengthy cycles and susceptibility to subjective biases. Generative approaches can rapidly produce thousands of design options for designers to screen and refine. By analysing data such as user reviews, purchasing behaviour, and search history, these methods build user preference models to generate designs tailored to target markets or specific user groups. Deep learning models learn from large image datasets to imitate human design strategies during creative and concept generation processes, implementing designers' black-box creative generation process in design problems with ambiguous rules and strategies. Among these methods, image generation models represented by GAN (Wang and Xue, 2024), diffusion models (Yue et al., 2024), and variational autoencoders (VAE) (Proteau et al., 2023) have been widely used in relevant research on industrial product design generation. Yang et al. (2023) proposed a product form design method based on diffusion models, generating numerous ear thermometer product form proposals using diffusion models, combined with SVM to filter the generated product schemes and addressing inconsistencies in design results during product form design. Yuan and Moghaddam (2020) processed and analysed smartwatch images for training GANs, designing an end-to-end design assistance system. Kang et al. (2023) proposed an emotionally enhanced design method combining deep convolutional generative adversarial networks (DCGAN), enabling mass production of conceptual social robot designs. Chen et al. (2025) developed a GAN model for generating anime character facial images, achieving high-quality batch generation of cartoon avatars. Jiang et al.

(2022) combined GAN and VAE to generate 3D product models from 2D product images, improving the generation of industrial product images. Ghasemi et al. (2024) proposed a GAN for industrial product generation, where the model enriches the texture of generated products under the influence of a perceptual loss function.

Although the functional and technological features of current industrial products have been continuously improved in the past, this is no longer sufficient to meet users' diverse needs. Users are increasingly focused on emotional experiences brought by products. However, due to the diversity of user aesthetic preferences and the complexity of emotional perception processes, it is not always possible for product designers to produce creative design solutions that satisfy users. Therefore, the primary contribution of this work lies not in the first-time use of GANs for design, but in the novel integration of a quantifiable emotional model with a GAN through a dedicated emotion-attention mechanism. This addresses the gap between high-level emotional needs and low-level visual feature generation. To this end, we propose an adversarial network simulation framework that evolves industrial product designs under the guidance of emotional resonance. The framework begins by constructing a quantifiable emotional space through the analysis of user reviews from e-commerce platforms. An improved SVR algorithm is then employed to establish a robust association between product design elements and user emotions, forming a predictive emotion evaluation model. The core of our design model integrates this emotional guidance directly into a generative adversarial network. This integration is achieved through a novel global emotional information extractor, which utilises a multi-head component attention mechanism to dynamically weigh the importance of each design component within the overall emotional context. This approach ensures the capture of nuanced user emotional needs and mitigates bias in the generated product imagery. Experimental results demonstrate the efficacy of this simulation, with the proposed method reducing the Fréchet inception distance (FID) and mean squared error (MSE) by at least 38.06% and 20.55%, respectively, compared to baseline methods, thereby offering a novel technical pathway for data-driven intelligent industrial product design.

This paper is organised into the following sections. Section 2 introduces the related theoretical foundations, including generative adversarial network and industrial product design development process. Section 3 proposes a method for associating product design elements with user emotion based on improved SVR. Section 4 proposes an industrial product design methodology that integrates user emotions with GAN. Section 5 depicts the experimental outcomes graphically and includes a comparative benchmarking. Section 6 summarises the key findings and suggests directions for future work.

2 Theoretical foundations for emotion driven design simulation

This section outlines the core theories linking GANs with industrial product design development processes, laying a theoretical foundation for subsequent model refinement and design methodology construction. It clarifies the convergence points and optimisation directions between GANs and affective design in industrial products.

2.1 Generative adversarial networks for design synthesis simulation

GAN is an important generative model in the field of deep learning, and its network structure includes a generator model and a discriminator model. Among them, the generator model is mainly responsible for investigating the distribution of sample data. To generate outputs as close as possible to real samples in the training set, it needs to randomly sample from the sample data space and use it as input. The discrimination model is generally a binary classifier; to make the output results of the generation network as similar as possible to real data, a discriminative network must be trained to distinguish between real samples and generated samples (Aggarwal et al., 2021). These two networks continuously adjust their parameters for adversarial training with the ultimate goal of making it impossible for the discrimination network to accurately determine whether a sample comes from real or generated data (Dang, 2025).

The principle of GAN is that two neural networks learn through mutual game play, solving the problem of unsolvable loss functions (Sajeeda and Hossain, 2022). The emergence of GAN has greatly promoted unsupervised learning and emotional image generation research; it has gradually expanded from initial image generation studies to various fields in computer vision. The objective function of GAN is shown in equation (1).

$$\min_G \max_D V(D,G) = E_{x\sim pdata(x)}[\log D(x)] + E_{z\sim pz(z)}[\log(1-D(G(z)))] \quad (1)$$

where $D(\cdot)$ is the discriminator, $G(\cdot)$ is the generator, E is the expected output, x is a real sample, and z is randomly input noise, $x\sim p_{data}(x)$ indicates that x comes from the real data distribution p_{data}, while $z\sim p_z(z)$ indicates that z comes from the prior distribution p_z. During adversarial training, the discriminator D attempts to maximise the value of equation (1), while the generator G tries to minimise it; when $D(G(z))$ equals 0.5, this corresponds exactly to the Nash equilibrium state, where the discriminator cannot distinguish whether a sample comes from real or generated data.

GANs directly optimise the realism of generated data through adversarial training between generators and discriminators. The discriminator, functioning as a dynamic loss function, provides real-time feedback on defects in generated data, compelling the generator to continuously refine its output. This adversarial-optimisation cycle enables GAN-generated samples to significantly outperform diffusion models and VAE in terms of rich detail and natural texture.

2.2 Design process evolution and simulation opportunities

In the field of industrial product design, initially, traditional design processes were followed; design proposals relied on designers' brainstorming. However, this method is limited by personal experience and imagination, unable to generate numerous creative proposals and suffering from low design efficiency (Lee and Chang, 2010). In the early stages, computers mainly intervened as auxiliary tools, aiming to enhance the efficiency of designers in physical model construction and visual effect presentation; although it indeed improved efficiency, it did not fundamentally change the overall framework of the design process. The evolution of industrial product design has progressed from traditional design to conceptual design and ultimately to product design, with each stage reflecting a distinct emphasis on user needs and technological capabilities. The core of product design remains deeply rooted in the integration of user needs and experience. The connection between critical design phases and users' emotional needs is manifested in the progressive relationship from functional fulfillment to emotional resonance. At its core, product design is user-centred, integrating multifaceted elements such as functionality, aesthetics, technology, and cost to create products that meet user needs and possess market competitiveness.

In the traditional design phase, designers usually need to communicate with clients or team members before beginning the design process to understand product requirements and target user groups. This includes gathering information about product functions, purposes, and user expectations. Afterward, based on the information from the requirement analysis phase, designers begin preliminary product design, which may involve sketches and conceptual designs to express the core functionality of the product (Hsueh et al., 2022). Once initial concepts are finalised, designers start design development to showcase the appearance, structure, and function of the product. Designers create physical models based on confirmed solutions for testing and verifying the design in practical use. Finally, they optimise and finalise the outcomes according to the results from testing.

Based on conceptual design, designers begin detailed design development, using design software to create more precise and elaborate design models that include all components of the product and their assembly methods. In the generative design phase, designers build parametric models, define design variables and constraints, and establish relationships between them. Subsequently, designers use design software to explore the design space by adjusting design parameters and optimisation objectives; the software generates numerous design solutions that meet specific requirements (Alcaide-Marzal and Diego-Mas, 2025). Among the large number of generated designs, designers evaluate and screen out preliminary solutions that align with the design goals (Li, 2025). From these filtered options, designers select the optimal solution and transform it into actual product design. Finally, after user testing and optimisation modifications, they finalise the solution.

Based on the core theories of GANs and industrial product design outlined above, and addressing the existing research challenge of imprecise mapping between emotional states and design elements, the following section will focus on constructing a methodological framework: First, an improved SVR model will be employed to establish precise correlations between design elements and user emotions. Subsequently, this correlation will be integrated into a GAN model to achieve emotion-driven product form generation.

3 Industrial product design elements and user emotional associations based on improved SVR

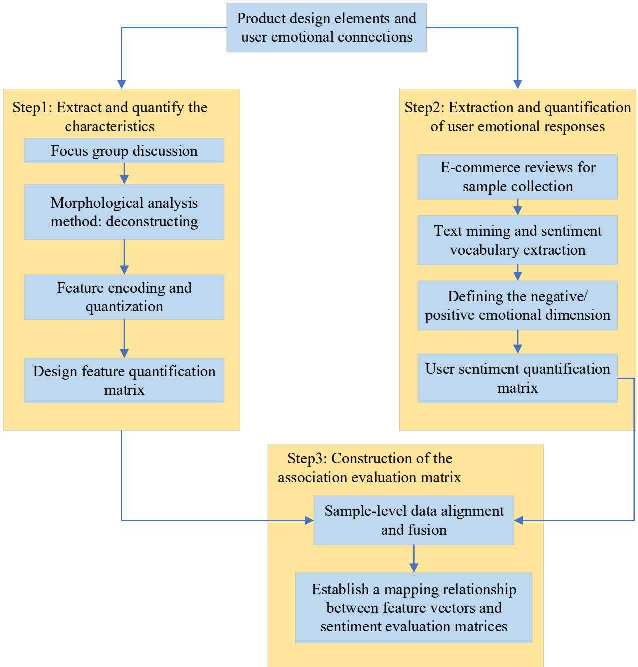
The core objective of this section is to establish a precise modelling method for the correlation between product design elements and users' emotional responses, providing clear quantitative support for subsequent simulations of form evolution under an emotional-oriented approach. Addressing the shortcomings of existing research, which failed to clearly model the input/output relationship and did not intuitively present the way design is related to emotions, this section clearly defines the correlation logic at the operational level, explicitly improves the input/output parameters of the SVR model, combines specific operational procedures, intuitively presents how product design characteristics are transformed into quantitative results of users' emotions through modelling, while retaining the core innovation points of kernel function improvement and parameter optimisation, ensuring the operability and academic rigor of the methodology.

3.1 User emotion-based product form feature evaluation matrix

In order to achieve the correlation between product design features and user emotional responses at the operational level, a standardised evaluation matrix for product form characteristics is first constructed as the basic carrier for the association modelling. The corresponding relationship between the quantification of design features and the quantification of emotional responses is clearly defined. The specific operation process is divided into three steps, as shown in Figure 1. At the same time, the core outputs of each step are defined to provide pre-support for the subsequent SVR modelling.

Step 1 Extract and quantify the characteristics. Through focus group discussions, 30 representative samples of the sub-products for this study were determined. Using the morphological analysis method, the product design characteristics at the operational level were decomposed into 4 major core quantifiable elements: contour shape, surface texture, colour combination, and component ratio. Each of the 4 major design characteristics of each sample was quantified and encoded one by one, forming a product design characteristic quantification matrix, which serves as one of the core input sources for subsequent association modelling.

Figure 1 The key process for constructing the evaluation matrix of product form features (see online version for colours)



Step 2 Extraction and quantification of user emotional responses. 1,200 user reviews from Amazon's after-sales evaluations were collected for the 30 samples. Emotional words were extracted through text mining technology. Combined with focus groups and hierarchical clustering methods, two major categories of core quantifiable emotional responses were selected, namely: positive emotions and negative emotions. 20 users were invited to rate each sample's two major categories of emotional responses. The average value was taken as the emotional quantification result of that sample, forming a user emotional response quantification matrix, which serves as the core output source for subsequent association modelling.

Step 3 Construction of the correlation evaluation matrix. The above-mentioned quantitative matrix of product design features and the quantitative matrix of user emotional responses are correspondingly integrated to construct a correlation evaluation matrix of product form characteristics and user emotions, clearly defining the one-to-one correspondence between each quantified value of the design feature and the corresponding quantified value of the emotional response. This enables the initial correlation between design features and emotional responses to be achieved at the operational level, providing a standardised dataset for subsequent SVR correlation modelling.

3.2 *Mapping the relationship between product design and user emotions*

Traditional linear models (such as principal component analysis) are unable to capture the complex nonlinear correlations between design characteristics and emotional responses. Moreover, the existing SVR modelling does not clearly define the input/output relationship, resulting in the implicit existence of the correlation. Therefore, this paper improves the SVR model by clearly defining the input/output parameters of the modelling at the operational level, clarifying the mapping logic of the correlation, and achieving a precise mapping from 'quantitative values of design characteristics to quantitative values of emotional responses'. The specific improvements and operational procedures are as follows. The entire process clearly defines the input and output, ensuring that the correlation logic is operable and reproducible.

In industrial product design, the SVR model is widely used to create correlations between product design elements and user emotions for predicting and classifying product emotion. However, during training, SVR requires computing and storing kernel matrices, whose size is proportional to the square of the number of samples. In addition, although SVR is known as a small-sample model, it can only accommodate small yet high-quality samples (with uniform distribution, low heterogeneity, and precise labels). If samples exhibit the aforementioned issues, it will directly cause the model's fitted mapping relationships to deviate from reality. For instance, the weighting of a certain design element's influence on warmth perception may be miscalculated, or even result in reverse mapping. When handling large-scale datasets, these kernel matrices become extremely large and consume significant memory space. To address the above issues, this paper improves the kernel function of the SVR model and introduces a variable neighbourhood search (VNS) algorithm (Lu et al., 2024) to optimise the parameters of the improved SVR model. The modified SVR algorithm is applied to mapping relationships between industrial product design elements and user emotions. Below is a specific description of the improvement process of SVR.

At the operational level, the input and output parameters of the SVR model are clearly defined, and the correlation mapping relationship between them is delineated. The specific definitions are as follows:

1 Input parameters. Clearly defined as a quantitative vector of product design characteristics, with a dimension of 1×4, representing the 4 major core design characteristic quantification values of a single sample (outline shape encoding, surface texture encoding, colour combination encoding, component ratio values). The value range of the input parameters is

strictly defined as: outline shape, surface texture, colour combination, component ratio, ensuring the standardisation of the input and avoiding modelling deviations.

2 Output parameters. Clearly defined as a quantitative vector of user emotional response, with a dimension of 1 × 2, representing the 2 major core emotional response quantification values of a single sample. The value range of the output parameters is strictly defined as 1–5 points, corresponding to the intensity levels of emotional responses (1 point is the lowest, 5 points is the highest).

3 Correlation mapping logic. Given any set of quantitative values of product design characteristics (which can be directly output the corresponding quantitative value of user emotional response through the model, intuitively presenting the correlation between design characteristics and emotional responses. At the same time, the model can be used to infer: if the desired emotional response is to be achieved, the range of corresponding quantitative values of design characteristics should meet, providing emotional constraints for subsequent form evolution simulation.

Kernel function selection is one of the key technologies for enhancing the predictive capability of SVR. Radial basis function (RBF) (Li et al., 2018) is the most commonly used kernel function because it can effectively map sample data from input space to a high-dimensional feature space. To achieve better performance predictors, this paper modifies RBF kernel functions by replacing Euclidean distance with geodesic distance. Let x_j be a nearest neighbour point of x_i, then the geodesic distance between x_j and x_i is defined as follows, where $d_e(x_i, x_j)$ represents the Euclidean distance between x_j and x_i.

$$d_G\left(x_i, x_j\right) = d_e\left(x_i, x_j\right) \tag{2}$$

If x_j is not a k-nearest neighbour point of x_i, but $\{x_{i,1}, x_{i,2}, \ldots, x_{i,k}\}$ is a k-nearest neighbour point of x_i, then the geodesic distance between x_j and x_i is as follows.

$$d_G\left(x_i, x_j\right) = \min\left\{d_e\left(x_i, x_{i,1}\right) + d_G\left(x_{i,1}, x_j\right), \cdots, d_e\left(x_i, x_{i,k}\right) + d_G\left(x_{i,k}, x_j\right)\right\} \tag{3}$$

Compared to Euclidean distance, geodesic distance can better reflect the shape information of sample distribution and more accurately express the actual distances between samples. Therefore, geodesic distance is more suitable for non-linear sampling point distribution surfaces. Kernel functions are divided into local kernel functions and global kernel functions; global kernel functions have weaker interpolation capabilities but stronger generalisation abilities. Compared to global kernel functions, local kernel functions only influence a small range of samples near the test points. The RBF kernel function is a typical local kernel function with weak generalisation ability but strong learning capability. For these properties mentioned above, improvements are made to the RBF kernel function by replacing Euclidean distance with geodesic distance. The improved RBF kernel function is as follows, where γ represents the balance factor, while t_1 and t_2 are regularisation parameters.

$$k_1\left(x_i, x_j\right) = \exp\left(-\gamma \cdot d_G\left(x_i, x_j\right)\right) \tag{4}$$

$$k_2\left(x_i, x_j\right) = \exp\left(-\gamma \cdot \left(d_G\left(x_i, x_j\right) + t_1\right) + t_2\right) \tag{5}$$

The kernel function $k_2(x_i, x_j)$ adds two regularisation parameters on the basis of $k_1(x_i, x_j)$, increasing the amplitude and displacement variation of the kernel function in order to further enhance its generalisation ability. Obviously, $k_1(x_i, x_j)$, $k_1(x_i, x_j)$, and $k_2(x_i, x_j)$ are all positive semi-definite functions; therefore they satisfy Mercer's theorem.

The main parameters in the SVR model are the penalty parameter c, insensitive loss parameter ε, and kernel parameter r. Selecting appropriate parameters can improve the accuracy of the model. To optimise the parameters in the improved SVR model, this paper introduces the VNS algorithm. First, according to Cherkassky (Lima et al., 2013), the initial solution for parameters c, ε and r is determined. Then a six-digit integer encoding is designed. Given the parameter range, the value of each parameter can be obtained by multiplying the encoding with corresponding coefficients. In addition, VNS explores the solution space more thoroughly by sampling increasingly larger neighbourhoods. Considering these two aspects, the neighbourhood structure in VNS is set as follows.

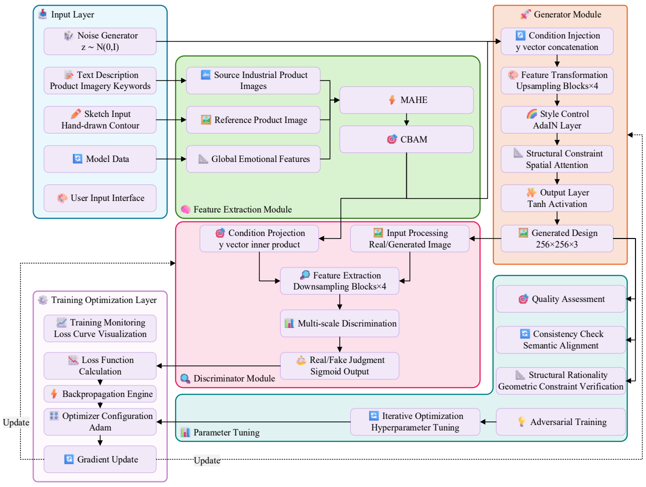
s_1, s_2 and s_3 are the encodings for c, ε and r respectively. $s = \{s_1, s_2, s_3\}$ is a solution set; a_1 and b_1 represent the minimum and maximum values that can be taken by x_i. $p_{ab}(c)$ is a function that ensures solutions after neighbourhood transformation can be mapped to the feasible solution space. The main purpose of the shaking process is to find a better neighbourhood for the current solution. During this phase, a new solution is randomly selected from the $N_k(s)$ structure around the current optimal solution s. Through this process, the optimal parameters c, ε, and r for SVR can be obtained, enabling an efficient mapping between product design and user emotions.

4 Industrial product design integrating user emotions and generative adversarial networks

4.1 The modelling and simulation framework for emotion-driven form evolution

An industrial product generation model is built based on an image generation model, which means that the image generation model needs to be trained to generate or create designs or appearances of industrial products. An image generation model is a type of deep learning model based on image generation algorithms, aiming to generate realistic image samples from random noise or specific inputs. Existing research ignores user emotional needs and struggles to capture local detail features of industrial products, leading to insufficient expression in the generated structure details. To address this issue, this paper proposes an industrial product design method integrating user emotions and GAN. The main workflow is shown in Figure 2.

Figure 2 Schematic of the proposed emotion conditioned generative adversarial network for industrial product design (see online version for colours)



Firstly, source industrial product images and reference product images are input into a feature extraction module to separately extract component content features and component emotional features. Then the global emotion information extractor extracts features from the source image while inputting target features to construct the global emotional feature expression of the source image. Finally, the target product image is generated and the model is optimised. The target image and the global emotional feature expression are jointly input into a generator, which captures and reconstructs high-level emotional semantic features to generate industrial product images meeting user emotional needs. At the same time, the target image is input into a discriminator for authenticity testing to distinguish differences between real and synthetic images, helping optimise model parameters.

4.2 *Feature extraction module*

The feature extraction module consists of a multi-head attention encoder, linear layer L, content classifier, and emotion classifier. First, the source product image is input into a multi-head self-attention encoder (MAHE) to capture rich local information from multiple perspectives of the source image, thereby extracting feature vectors for each local component $F_i = \{F_1, F_2, \ldots, F_k\}$. Second, $F_i = \{F_1, F_2, \ldots, F_k\}$ is input into linear layer L to perform refined separation and integration of the local features. This process aims to decouple mixed local features into local content features and local emotion features. The content features focus on retaining the original semantics of the image, while the emotional features emphasise artistic expressions such as form characteristics, thickness variations, and decorative details unique to images.

Finally, to ensure effective decoupling between content and emotional features, the local component content features and local component emotion features are further input into a style classifier and an emotion classifier. Through in-depth learning and discrimination of local features, they precisely extract the component content features from the source product image $f_c = \{f_{c,1}, \ldots, f_{c,k}\}$, eliminating redundant information associated with emotions. Similarly, reference glyphs undergo exactly the same processing flow to obtain their component emotion features $f_s = \{f_{s,1}, \ldots, f_{s,2}\}$, removing redundant information related to semantics.

MAHE aims to utilise heads to extract the local component features of glyph forms, enabling a complex product image to be fully expressed by multiple local features specified. MAHE consists of six heads, each composed of four residual blocks and two convolutional block attention module (CBAM) modules that fuse channel attention with spatial attention. Among them, the design of the residual block helps alleviate gradient vanishing and exploding issues when network layers are stacked deeper, enhancing feature propagation. Formally, the multi-head encoder takes an industrial product image X as input and uses the multi-head encoder E_i to extract local component features $F_i \in R^{d \times w \times h}$, as shown in equation (6), where F_i is the local component feature extracted by the i^{th} head attention encoder E_i, $i = 1, 2, \ldots, k$ is the number of heads in MAHE, d is the feature dimension, and $w \times h$ is the spatial dimension.

$$F_i = E_i(X) \tag{6}$$

To better decouple content features and emotion features of components, a content classifier C_u and an emotion classifier C_s are set up. The classifiers maintain consistent architectures, both consisting of two residual blocks, an average pooling layer, and a dropout layer. Among them, each residual block consists of two convolutional layers with a filter size of 3 × 3, stride 1, and padding 1.

Formally, the content and emotion classifiers first apply a linear projection to F_i to disentangle the emotional and content aspects. The content feature $f_{c,i}$ and the emotional feature $f_{s,i}$ of the component are obtained as follows.

$$\left(f_{c,i} f_{s,i}\right) = L\left(F_i\right) \tag{7}$$

where $f_{c,i}$ and $f_{s,i}$ are both input into C_u and C_s to achieve the prediction of emotion while misleading the content classifier C_u for classifying contents, ultimately achieving consistent prediction. Maximum entropy of predictive probability is selected to realise consistency in prediction, which encourages classifiers to generate more certain prediction results and reduces inconsistency in predictions by the classifier on uncertain samples, aiming to improve model stability. The objective function $L_{s,i}(f_{s,i}, y_s)$ of $f_{s,i}$ is as follows, where CE represents cross-entropy loss, and y_s is the emotion label.

$$L_{s,i}\left(f_{s,i}, y_s\right) = CE\left(C_s\left(f_{s,i}\right),\ y_s\right) - H\left(C_u\left(f_{s,i}\right)\right) \tag{8}$$

The objective function $L_{c,i}(f_{c,i}, U_c)$ of $f_{c,i}$ is computed as follows, where U_c is the component set label of the input industrial product image.

$$L_{c,i}\left(f_{c,i}, U_c\right) = \sum_{j \in U_c} \omega_{ij} CE\left(C_u\left(f_{c,i}\right), j\right) - H\left(C_S\left(f_{c,i}\right), j\right) \quad (9)$$

Leveraging the independence loss between $f_{c,i}$ and $f_{s,i}$ ensures separation between component content and emotion features, shown below.

$$L_{indp,i} = HSIC\left(f_{s,i}, f_{c,i}\right) \quad (10)$$

4.3 *Global emotion information extractor*

According to the characteristics of industrial product images, there exist certain positional relationships among components. Capturing structural information between these components can assist the generator in focusing on such positional relationships during image reconstruction. To capture global emotional information of component features, the proposed model constructs a multi-head component attention module. Formally, $f_c = \{f_{c,i} | i = 1, 2, \ldots, k\}$ is used as an input vector for component content features to reconstruct query vectors Q_i^m, key vectors K^m, and value vectors V^m, shown below, where W_Q, W_K, and W_V are mapping weight parameters. *m* denotes that the multi-head component attention module has m heads, and F_p is the global emotion information feature.

$$Q_i^m = f_{c,i} W_Q, K^m = F_p W_K, V^m = F_p W_V \quad (11)$$

The relationship weights between component features and global emotion information are calculated as shown in equation (12) and equation (13), where A^m represents the correlation between component features and global emotions, K^m is the key vector, c is the dimension of input vectors, c^m is a scaling factor, m is the number of attention heads.

$$A^m = \frac{Q_i^{m^T} K^m}{\sqrt{c^m}} \quad (12)$$

$$\alpha^m = softmax\left(A^m\right) \quad (13)$$

The value from multiplying α^m with V^m is used to aggregate component information features and global emotion information features, as shown in equation (14).

$$S^m = \alpha^m V^{m^T} \quad (14)$$

Finally, each attention output is combined by concatenating the m-head information along the channel dimension, and linear projection L_s captures inter-component emotional features F_l, as shown below.

$$F_l = L_s\left(S^1; S^2; \ldots; S^m\right) \quad (15)$$

4.4 *Adversarial training*

During adversarial training, the generator takes target features F_t, F_l and F_g as inputs to generate a final target image $\tilde{a}$. Here, F_t is derived by MAHE through concatenating all component content and component emotion features. The calculation is as follows.

$$F_t = \left[\left(f_{s,1}; f_{c,1}\right), \ldots, \left(f_{s,k}; f_{c,k}\right)\right] \quad (16)$$

The target industrial product image $\tilde{a}$ is calculated as follows, where G represents the generator and ';' denotes a concatenation operation.

$$\tilde{a} = G\left(F_t; F_l, F_g\right) \quad (17)$$

The discriminator is responsible for determining the authenticity of the generated network output $\tilde{a}$, helping the generator continuously optimise the realism and quality of the generated images to achieve high-quality industrial product images. The entire model obtains high-quality images through adversarial loss. Discriminator adversarial loss L_{adv}^D and generator adversarial loss L_{adv}^G are calculated as follows, where a is the target image label, y_s is the emotion label, and y_c is the content label.

$$\begin{aligned} L_{adv}^D = & E_{(a, y_c, y_s)}\left[\left[1 - D\left(a, y_s\right)\right]_+ + \left[1 - D\left(a, y_c\right)\right]_+\right] \\ & + E_{(\tilde{a}, y_c, y_s)}\left[\left[1 - D\left(\tilde{a}, y_s\right)\right]_+ + \left[1 - D\left(\tilde{a}, y_c\right)\right]_+\right] \end{aligned} \quad (18)$$

$$L_{adv}^G = -E_{(\tilde{a}, y_c, y_s)}\left[D\left(\tilde{a}, y_s\right) + D\left(\tilde{a}, y_c\right)\right] \quad (19)$$

Adversarial training forces the generator to continually explore the boundaries of the design space through a dynamic game with the discriminator, breaking through the limitations of traditional design methods to generate more innovative design solutions. By introducing adversarial examples, adversarial training enables the generator to learn to produce designs insensitive to perturbations, thereby enhancing design robustness. In industrial product design, this means generated designs can better withstand various uncertainties encountered in real-world use, such as environmental changes and user operating habits.

5 Experimental validation and analysis of the simulation framework

5.1 *Dataset and experimental environment*

The data of this article comes from the Amazon shopping platform, which can basically cover most product data and is sufficient to grasp current product design trends. Web crawlers are programs that automatically extract data from websites according to certain rules; researchers often use this technique to obtain specific data existing on particular websites. Small electronic products were chosen as crawling targets, and a total of 160,000 images along with their information such as brand, name, and category were collected using crawler technology. To build high-quality training data, we carried out the following standardised preprocessing procedures.

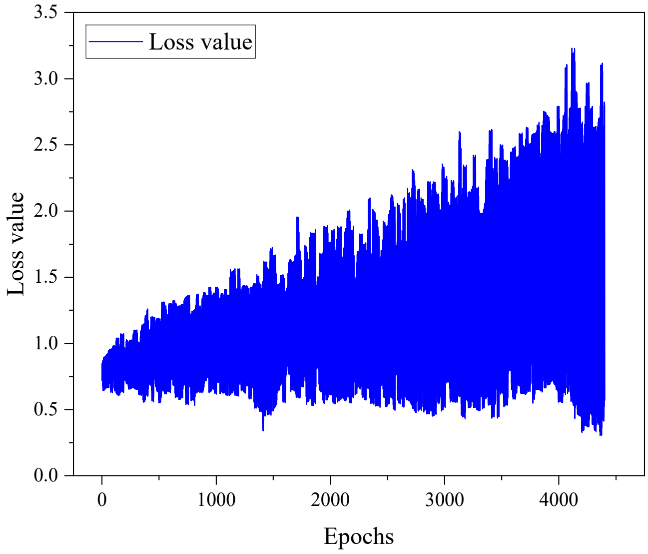
All images were uniformly scaled to 200 × 200 pixels. A frequency-coordinated visual saliency detection and edge detection algorithm was adopted to automatically identify and batch remove images with messy backgrounds and unobtrusive subjects. The perceptual hashing algorithm was applied for pairwise image comparisons, and duplicate or highly similar samples were removed. After cleaning, the dataset contained 64,893 valid images, covering 16 categories such as headphones, smartwatches, and Bluetooth speakers, involving over 4,000 brands. This study was randomly divided into training set, validation set, and test set in a 6:2:2 ratio to ensure the fairness of the evaluation. The sorting code and data partition list of this dataset will be publicly released on GitHub after the acceptance of the paper.

The experiments were conducted in a Windows 10 operating system environment equipped with an AMD EPYC 7551 64-core 2.0GHz processor and an Nvidia GTX 3070Ti GPU. The experimental development environment selected PyCharm as the integrated development platform for Python. The deep learning framework used was the PyTorch-GPU version developed by Facebook, which is built upon the Anaconda integrated library with a clean and flexible interface design and efficient and stable processing capabilities. In addition, the experiments also utilised CUDNN 7.6 and CUDA 10.1 as GPU acceleration platforms. The Adam optimiser was used to optimise the proposed model MAHE. The discriminator learning rate was set to 10^{-3}, while the learning rates for all other modules were set to 2×10^{-4}. The number of multi-head attention encoders was set to $k = 6$, and the training model went through 650k iterations.

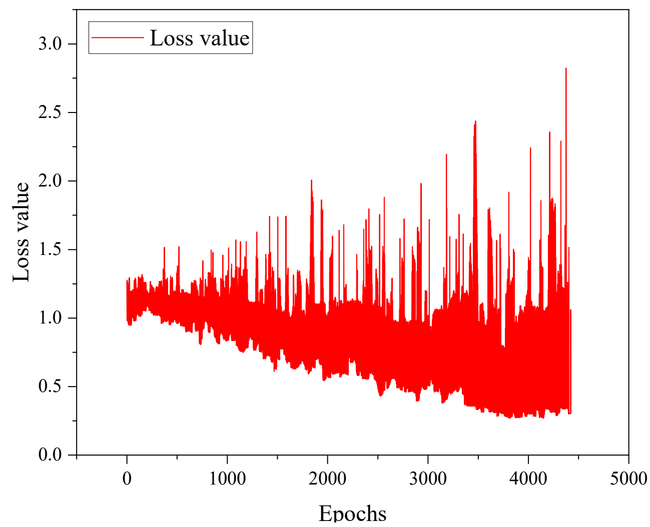
5.2 *Loss performance analysis of the generator and discriminator*

Figure 3(a) and Figure 3(b) respectively represent the loss variations of the generator and discriminator in the MAHE model during the training process. From the loss curves of the training set and test set, it can be observed that the initial stage is relatively smooth; as the number of iterations increases, the model continuously engages in adversarial learning, resulting in fluctuating loss values shown in the figure, indicating that the model gradually becomes stable. Figure 3(b) represents the change in classification loss for real data within the discriminator. In the early stages, the model was not mature and the classifications were inaccurate. As the discriminator model improved, the loss value continuously decreased, eventually reaching a state of convergence. Since the generator and discriminator are constantly adversarial, when the generator is stronger than the discriminator, the discriminator's classification performance is poor, resulting in the sudden increase of classification loss shown in Figure 3(b).

Figure 3 The changes in the generator and discriminator losses of the MAHE model, (a) loss of the generator and (b) the loss of the discriminator (see online version for colours)



(a)



(b)

5.3 *Performance comparison with other algorithms*

For the goal of hensively evaluate the generation performance of the proposed method (MAHE), we conducted quantitative and qualitative comparisons with four mainstream generation methods. Figure 4 is usually presents the product image samples generated by each method under the same set of emotional target inputs. The images generated by our method are superior to those of the baseline method in terms of morphological consistency, detail completeness, and emotional expression.

To explore the differences between the MAHE method and mainstream product design methods, this section compares it with the CNN-GAN method (Kang et al., 2023), CSGAN method (Chen et al., 2025), DMGAN method (Jiang et al., 2022), and DCG-GAN method (Ghasemi et al., 2024). The experiments selected Structural

Similarity Index Measure (SSIM),Peak Signal-to-Noise Ratio (PSNR), FID, MSE, and Mean Absolute Error (MAE) as evaluation metrics. These metrics can all measure the similarity between generated industrial product images and real product images. A higher SSIM value, a higher PSNR value, a lower FID value, a lower MSE value, and a lower MAE value indicate that the generated results are more similar to the real results. The generation results of different methods for industrial products are shown in Table 1.

Figure 4 Comparison of industrial product images generated by different methods under the same emotional goal driving force

Table 1 The generation results of different methods for industrial products

Method	*SSIM*(↑)	*PSNR*(↑)	*FID*(↓)	*MSE*(↓)	*MAE*(↓)
CNN-GAN	0.734	6.719	118.687	22.434	39.371
CSGAN	0.760	7.038	105.549	21.219	34.828
DMGAN	0.731	6.271	99.929	20.472	34.763
DCG-GAN	0.744	6.438	53.025	14.365	33.315
MAHE	0.821	8.096	32.842	9.237	26.468

As shown in Table 1, the SSIM evaluation index of the generated results using MAHE method is higher by 11.85%, 8.03%, 12.31%, and 10.35% compared to CNN-GAN, CSGAN, DMGAN, and DCG-GAN, respectively. The PSNR evaluation index of the generated results using MAHE method is higher by 20.49%, 15.03%, 29.10%, and 25.75% compared to CNN-GAN, CSGAN, DMGAN, and DCG-GAN, respectively. Comparing the FID index further, MAHE method reduces it by 72.33%, 68.88%, 67.13%, and 38.06% compared to CNN-GAN, CSGAN, DMGAN, and DCG-GAN, respectively. Comparing the generation accuracy index further, the MAE and MSE of MAHE method are 9.237 and 26.468, which decrease by 58.83% and 32.77%, respectively, compared to CNN-GAN; they reduce by 56.47% and 24.00%, respectively, compared to CSGAN; they decline by 54.88% and 23.86%, respectively, compared to DCG-GAN. Compared to other contrast methods, MAHE method demonstrates significant advantages across four evaluation indices, indicating that the algorithm presented in this section has excellent industrial product image generation capabilities.

After 1,000 independent runs, the mean and standard deviation of the FID index for industrial product generation were obtained. In addition, this paper uses the well-known Wilcoxon rank-sum test to analyse the results, where '+', '–', and '≈' indicate that the comparison method is significantly better than MAHE, significantly worse than MAHE, or statistically similar to MAHE, respectively. The results of the FID index and the Wilcoxon rank-sum test are shown in Table 2. It can be seen that the maximum, minimum, mean, and standard deviation of the FID index for MAHE are all lower than those of the comparison methods, indicating that MAHE significantly outperforms several other methods in product image quality generation. The experimental results show that the MAHE method performs well in industrial product design.

Table 2 The results of the FID index and the Wilcoxon rank-sum test

Method	*Mean value*	*Standard deviation*	*Maximum*	*Minimum*	*Significance test*
CNN-GAN	147.831	118.687	172.984	112.639	–
CSGAN	132.489	105.549	147.912	98.431	–
DMGAN	111.952	99.929	136.921	92.513	–
DCG-GAN	60.963	53.025	62.841	39.651	–
MAHE	34.159	32.842	40.683	30.258	

5.4 *Affective visualisation analysis of industrial product design*

To better display the affective resonance feature visualisation analysis for GAN-simulated industrial product designs, this paper uses T-SNE to analyse the affective feature visualisations of CSGAN, DMGAN, DCG-GAN, and MAHE, as shown in Figure 5, where blue points represent negative emotions and orange points represent positive emotions. When points of the same colour are closer together, it indicates that they are semantically more similar and produce better emotional resonance evolution. It can be observed that Figure 5(d) shows that the MAHE method achieves the best fusion representation and clustering effect, while Figure 5(c) achieves a suboptimal result. Compared to Figure 5(d), the multimodal features in Figure 5(a) and Figure 5(b) tend to become more dispersed. CSGAN is based on fully convolutional networks and can process image emotional features, but it has weak support for complex geometric structures or non-image emotional data in industrial products. The DMGAN method is based on GAN and VAE to design industrial products, but the emotional analysis is weak and cannot generate industrial products that match user emotions. DCG-GAN generates industrial products based on user emotion and perception GAN. However, existing methods may have difficulty accurately capturing subtle differences in user emotions, leading to generated designs that do not precisely meet users' emotional needs. MAHE proposes a multi-head component attention module to help the model learn correlations between components and global emotional features, allowing the model to more specifically understand and learn interrelationships of components under global emotional features.

5.5 *Ablation experiment*

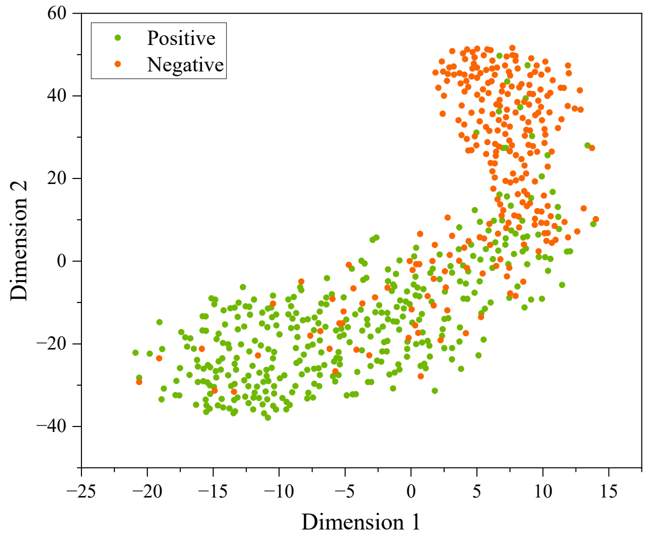
To analyse the effectiveness of key designs within the proposed framework, we conducted systematic ablation experiments, with results shown in Table 3.

- w/o attention. Removing the multi-head attention module from the component and directly concatenating emotion features resulted in significant increases in FID and MSE, indicating that this module is crucial for achieving precise emotion pattern control by modelling component weights.
- w/o LG. Removing the independence loss. Insufficient decoupling of content and emotion features led to decreased content fidelity (SSIM) in generated images, validating this loss's effectiveness in separating semantic and stylistic information.
- w/o improved SVR: replacing the emotion prediction model with standard SVR. All metrics deteriorated, proving that the improved SVR model's more accurate emotion quantification is fundamental to high-quality generation.

Table 3 The results of the ablation experiment

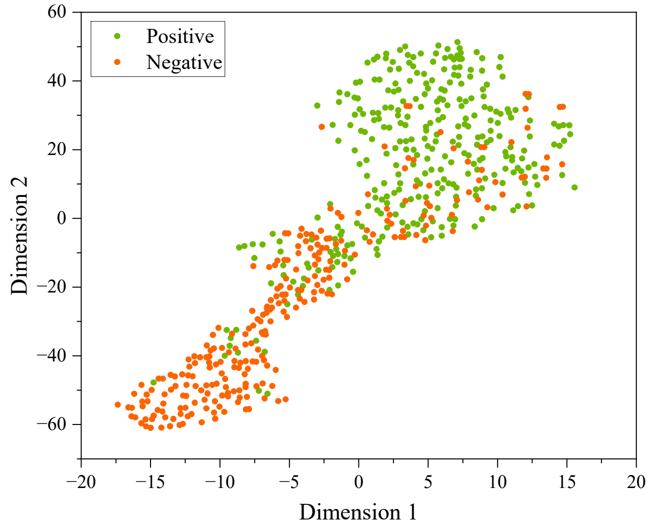
Model variants	*FID (↓)*	*MSE (↓)*	*SSIM (↑)*
w/o attention	51.676	14.561	0.795
w/o LG	41.328	11.893	0.803
w/o improved SVR	38.752	10.971	0.812
MAHE	32.842	9.237	0.821

Figure 5 Visualisation of emotional features in different models, (a) CSG AN (b) DMGAN (c) DCG-GAN and MAHE (see online version for colours)

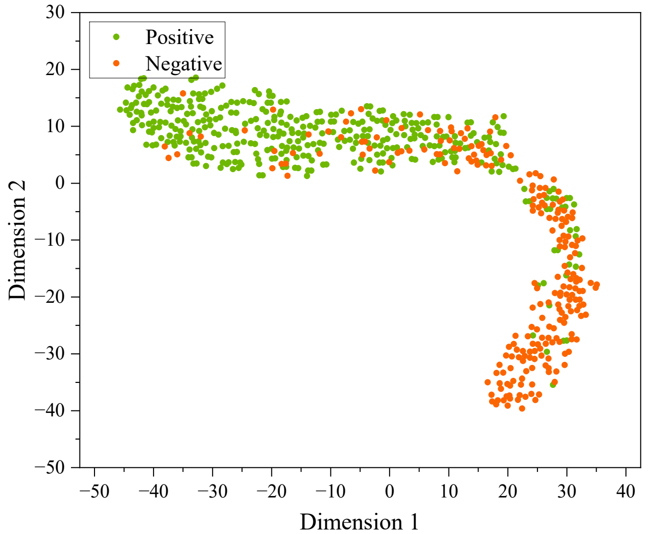


(a)

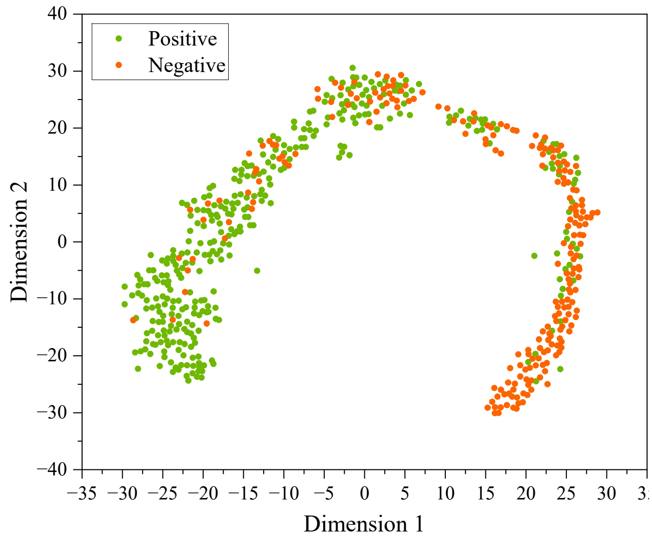
Figure 5 Visualisation of emotional features in different models, (a) CSG AN (b) DMGAN (c) DCG-GAN and MAHE (continued) (see online version for colours)



(b)



(c)



(d)

6 Conclusions

Emotional resonance in industrial product design is crucial for enhancing user satisfaction and brand loyalty. However, existing research ignores user emotional needs and has difficulty capturing detailed characteristics of industrial products, resulting in insufficient expression of structural details in generated designs. To address these issues, this paper proposes a generative adversarial network simulation method to evolve the emotional resonance form of industrial product design. The main work achievements of this method are as follows.

1 Analysed user emotional needs from post-sale user reviews on e-commerce platforms and construct a product emotion space. Build an improved SVR algorithm to establish correlations between product design elements and user emotions, thus constructing a product emotional evaluation model.

2 Improved the kernel function of the SVR model and introduced a variable neighbourhood search algorithm to optimise the parameters of the improved SVR model. The enhanced SVR algorithm was applied to map relationships between industrial product design and user emotions.

3 Proposed an integrated product design model combining user emotion with GAN. A new global emotional information extractor was designed, along with multi-head component attention used to focus on the varying importance of each component within global emotional information in order to capture users' emotional needs and avoid deviations in generated product images.

4 Simulation experiments were conducted on a real dataset. Results showed that the FID of the proposed method was 32.842, representing reductions of 38.06%–72.33% compared to baseline methods. This provides an intelligent tool and theoretical support for emotion-based design in industrial products.

Although this study has achieved certain advances in the field of industrial product design, there are still areas needing improvement. Future work will focus on two main directions.

First, current research faces challenges in accurately modelling and quantifying users' complex and diverse emotions. In the future, knowledge from multiple disciplines such as psychology and cognitive science can be integrated to deeply explore the underlying mechanisms of emotion generation and develop a more detailed and comprehensive system for emotional quantification indicators. For example, physiological signal acquisition techniques like EEG and eye tracking can be used to capture real-time user emotional responses to product forms. These physiological data can then be combined with subjective emotional evaluations to build more precise emotional models, allowing GANs to generate product forms that better align with users' emotional needs based on more accurate emotional input.

Second, the current research is mainly based on image data. In the future, multimodal generative models can be introduced to integrate diverse information such as product sketches, 3D models, material textures, and even design description texts for joint training. This will allow a more comprehensive and detailed capture of design elements related to emotional resonance, enabling the generation of solutions with greater depth and detail.

Declarations

All authors declare that they have no conflicts of interest.

References

Aggarwal, A., Mittal, M. and Battineni, G. (2021) 'Generative adversarial network: an overview of theory and applications', *International Journal of Information Management Data Insights*, Vol. 1, No. 1, pp.14–27.

Alaniz, T. and Biazzo, S. (2019) 'Emotional design: the development of a process to envision emotion-centric new product ideas', *Procedia Computer Science*, Vol. 158, pp.474–484.

Alcaide-Marzal, J. and Diego-Mas, J.A. (2025) 'Computers as co-creative assistants. A comparative study on the use of text-to-image AI models for computer aided conceptual design', *Computers in Industry*, Vol. 164, pp.104–118.

Buker, T., Schmitt, T., Miehling, J. and Wartzack, S. (2023) 'Exploring the importance of a usable and emotional product design from the user's perspective', *Ergonomics*, Vol. 66, No. 5, pp.580–591.

Chao, C., Chen, Y., Wu, H., Wu, W., Yi, Z., Xu, L. and Fu, Z. (2023) 'An emotional design model for future smart product based on grounded theory', *Systems*, Vol. 11, No. 7, pp.37–41.

Chen, C. (2024) 'Application of support vector machine–based CNC machining in furniture product visual design and production control process', *The International Journal of Advanced Manufacturing Technology*, Vol. 5, pp.1–9.

Chen, Y.-C., Shibata, H. and Takama, Y. (2025) 'Generation of comic style chernoff face with GAN', *Journal of Advanced Computational Intelligence and Intelligent Informatics*, Vol. 29, No. 2, pp.396–406.

Dang, L. (2025) 'Financial risk prediction and warning system based on SGAN deep learning', *International Journal of Information and Communication Technology*, Vol. 26, No. 37, pp.1–17.

Gao, Z. and Huang, J. (2022) 'Human-computer interaction emotional design and innovative cultural and creative product design', *Frontiers in Psychology*, Vol. 13, pp.23–45.

Ghasemi, P., Yuan, C., Marion, T. and Moghaddam, M. (2024) 'DCG-GAN: design concept generation with generative adversarial networks', *Design Science*, Vol. 10, pp.10–19.

Hsueh, S-L., Zhou, B., Chen, Y-L. and Yan, M.-R. (2022) 'Supporting technology-enabled design education and practices by DFuzzy decision model: applications of cultural and creative product design', *International Journal of Technology and Design Education*, Vol. 32, No. 4, pp.2239–2256.

Hughes, R.T., Zhu, L. and Bednarz, T. (2021) 'Generative adversarial networks–enabled human–artificial intelligence collaborative applications for creative and design industries: a systematic review of current approaches and trends', *Frontiers in Artificial Intelligence*, Vol. 4, pp.60–74.

Jiang, Z., Wen, H., Han, F., Tang, Y. and Xiong, Y. (2022) 'Data-driven generative design for mass customization: a case study', *Advanced Engineering Informatics*, Vol. 54, pp.101–116.

Kang, X., Nagasawa, S.y., Wu, Y. and Xiong, X. (2023) 'RETRACTED: emotional design of bamboo chair based on deep convolution neural network and deep convolution generative adversarial network', *Journal of Intelligent and Fuzzy Systems*, Vol. 44, No. 2, pp.1977–1989.

Kusiak, A. (2020) 'Convolutional and generative adversarial neural networks in manufacturing', *International Journal of Production Research*, Vol. 58, No. 5, pp.1594–1604.

Lee, J.-H. and Chang, M.-L. (2010) 'Stimulating designers' creativity based on a creative evolutionary system and collective intelligence in product design', *International Journal of Industrial Ergonomics*, Vol. 40, No. 3, pp.295–305.

Li, M. (2025) 'A simulation-based modelling framework for personalised design using an improved generative adversarial network', *International Journal of Simulation and Process Modelling*, Vol. 22, Nos. 3–4, pp.160–170.

Li, X., Gong, C., Gu, L., Gao, W., Jing, Z. and Su, H. (2018) 'A sequential surrogate method for reliability analysis based on radial basis function', *Structural Safety*, Vol. 73, pp.42–53.

Lima, A.R., Cannon, A.J. and Hsieh, W.W. (2013) 'Nonlinear regression in environmental sciences by support vector machines combined with evolutionary strategy', *Computers and Geosciences*, Vol. 50, pp.136–144.

Liu, X., Yang, S. and Wu, Y. (2023) 'Product emotional design method based on image metaphor: a technical note', *Journal of Engineering Design*, Vol. 34, No. 2, pp.180–201.

Lu, S., Ma, C., Liu, X. and Pardalos, P.M. (2024) 'Scheduling identical serial-batching machines in the engine manufacturing supply chain by an integrated variable neighbourhood search algorithm', *Computers and Operations Research*, Vol. 164, pp.52–67.

Norman, D.A. (2004) 'Introduction to this special section on beauty, goodness, and usability', *Human–Computer Interaction*, Vol. 19, No. 4, pp.311–318.

Proteau, A., Tahan, A., Zemouri, R. and Thomas, M. (2023) 'Predicting the quality of a machined workpiece with a variational autoencoder approach', *Journal of Intelligent Manufacturing*, Vol. 34, No. 2, pp.719–737.

Sajeeda, A. and Hossain, B.M. (2022) 'Exploring generative adversarial networks and adversarial training', *International Journal of Cognitive Computing in Engineering*, Vol. 3, pp.78–89.

Stafford, C., Provost, K. and Jones, N. (2025) 'Model validation levels: an automatable framework for model validation', *Journal of Simulation*, Vol. 8, pp.1–18.

Sun, H., Ma, Q., Chen, Z. and Si, G. (2023) 'A novel decision-making approach for product design evaluation using improved TOPSIS and GRP method under picture fuzzy set', *International Journal of Fuzzy Systems*, Vol. 25, No. 4, pp.1689–1706.

Wang, Y. and Xue, Q. (2024) 'Fault identification of product design using fuzzy clustering generative adversarial network (FCGAN) model', *Soft Computing*, Vol. 28, No. 4, pp.3725–3742.

Wu, Z., Tan, J., Wu, H. and Zha, W. (2025) 'Generative adversarial network model-based knowledge recommendation with knowledge graph in product design', *Journal of Engineering Design*, Vol. 6, pp.1–31.

Yang, C., Liu, F. and Ye, J. (2023) 'A product form design method integrating Kansei engineering and diffusion model', *Advanced Engineering Informatics*, Vol. 57, pp.58–71.

Yang, S. (2019) 'The study of customer experience design and optimization of shopping website: case analysis of Amazon in China', *Asian Business Research*, Vol. 4, No. 2, pp.1–13.

Yu, B., Yang, Y. and Liu, X. (2025) 'Intelligent optimisation of traditional village element layout using generative adversarial networks', *International Journal of Information and Communication Technology*, Vol. 26, No. 30, pp.60–80.

Yuan, C. and Moghaddam, M. (2020) 'Attribute-aware generative design with generative adversarial networks', *IEEE Access*, Vol. 8, pp.190710–190721.

Yue, Z., Wang, J. and Loy, C.C. (2024) 'Efficient diffusion model for image restoration by residual shifting', *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 47, No. 1, pp.116–130.