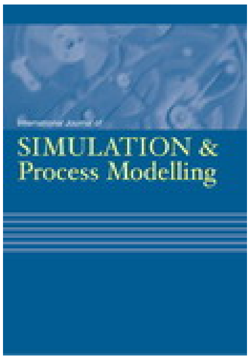

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A simulation-based modelling framework for personalised design using an improved generative adversarial network

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Abstract: As a key component of the creative sector, art typeface design has progressively taken front stage given the growing demand for customised design. Manual design is common in traditional font design, which takes time and cannot rapidly adjust to individual needs. This paper presents StyleGANFont, a personalised art font design model based on improved generative adversarial network (GAN), which is capable of producing high-quality, diversified and personalised art fonts by means of multi-level style control, adaptive personalisation modelling and real-time user feedback to meet the demand for fast and tailored font design. To create typefaces, StyleGANFont has clear benefits according to the comparison and ablation experiments. At last, this work also addresses the direction of next research to support the continuous advancement of personalised art font generating technologies.

Keywords: personalised art font generation; improved GAN; multi-level style control; user-preference modelling.

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1 Introduction

1.1 Background of study

Digital and visual design has entered all spheres of life with the full arrival of the information age, particularly in the domains of the internet, advertising, social media and brand promotion, which play a crucial role in conveying information. Fonts are one of the fundamental components of graphic design; they not only serve the simple purpose of displaying textual information but also are indispensable in visual art (Günay, 2024). Font selection and degree of matching with the general design style strongly influence the design effect and user experience whether in web design, product packaging, or advertising.

Although this method can guarantee a great degree of artistry and inventiveness, there are several restrictions in practical application; traditional font design mainly depends on designers' hand creation and adjustment. First, font creation is a very time-consuming and labour-intensive procedure; in particular, manual design is sometimes challenging to effectively satisfy the needs of a great number of users considering personalised requirements. Second, font design itself has a high technical barrier, hence designers must have thorough professional experience in glyphs, strokes, spacing, symmetry, and other elements (Xiao et al., 2023). Furthermore, conventional techniques have been challenging to keep up with the fast-growing market need and there is a pressing need to create new technical means to achieve more efficient and flexible font design in addition to the increasing customised and diversified wants.

With the fast growth of artificial intelligence (AI) in the 21st century, computer vision and image processing have experienced advances. Regarding font design, generative adversarial network (GAN) enables the creation of unique art typefaces feasible. Typical typeface design obstacles are mostly expressed in low design efficiency, inadequate customised expression and slow response to market demand (Tofail et al., 2018). By learning from a vast number of font samples without depending on labour-intensive manual procedures, GAN-based font generating methods can automatically develop tailored fonts that satisfy consumers' needs. This not only considerably increases the efficiency of font design but also modifies style, structure, and features of typefaces depending on the user's specific needs, so greatly extending the creative area of font design.

Though the GAN-based font generating technique offers fresh chances for font creation, actual use presents various difficulties. First, the customised generation of fonts has to consider multi-dimensional design requirements including the stylistic variations of fonts and the harmony between aesthetics and usefulness of fonts. The present GAN approach still suffers with issues including inconsistent generating effect when creating typefaces and inadequate detail processing (Habeeb et al., 2024). The second question is how to stylise fonts under the assumption of ensuring their readability and how to make the produced fonts really fit the individual needs of diverse users. Thus, a major focus of present research is on how to improve the structure of GAN and apply it in font creation.

Overall, tailored art font creation based on GAN is not only a technological advance in the design industry in the new era but also a crucial study direction in the field of computer vision. More effective and personalised font generation can be attained by optimising and improving the GAN model, therefore creating a whole new universe for typeface design and visual communication. This work intends to investigate the application of GAN in personalised creative font design by means of improved GAN, so addressing the shortcomings of the current technology, and providing theoretical support and practical advice for the realisation of intelligent font design.

1.2 Innovations in study

This work is intended to provide a personalised art font design approach based on improved GAN, therefore transcending the constraints of conventional font design techniques and offering a more efficient and flexible alternative for personalised font generating. This study is notably new in the following respects when compared with previous studies:

1 Improved GAN architecture design: This work suggests improved GAN architecture with a multi-level style control module and an adaptive training mechanism so that the generator may better manage the details and personalising needs of fonts. This invention not only raises the quality of the produced fonts but also increases the stability and efficiency of the producing process.

2 Accurate modelling of personalised requirements: This work introduces the user preference learning module to enable the GAN to dynamically adjust depending on the customised information given by the user (design style, font thickness, font shape modification, etc.). Thus, correct production of personalised fonts is achieved. This invention can better satisfy the needs of many users and significantly increase adaptability and variation in font design.

3 Optimisation mechanism combined with user feedback: This paper suggests an online optimisation technique based on user feedback that can continuously modify the model generating approach depending on the evaluation of the fonts, hence progressively improving the quality and compliance of the fonts. This approach guarantees a high match between the produced fonts and users' needs, efficiently achieves dynamic optimisation, and increases interactivity and user involvement in the design process.

In summary, this work effectively uses GAN in the field of personalised art font design by improving it, so it not only solves the shortcomings of conventional design methods in terms of efficiency and personalisation but also enhances the artistry and practicability of font design and offers a significant reference and theoretical support for the future development of intelligent font generating technology.

This paper is organised as follows: Section 2 reviews GAN variants; Section 3 discusses personalised typography; Section 4 presents the proposed StyleGANFont model; Section 5 gives experiments; Section 6 concludes and outlines future work.

2 Generative adversarial network

GAN is a deep learning (DL) model that has grown to be a major generative modelling accomplishment (Purwono et al., 2025). GAN's central concept is to use adversarial training to play a game between generating and discriminative models, therefore allowing the generator to generate increasingly near-to-actual data. While the discriminator is employed to tell whether the incoming data is actual data or created data, the generator's job is to create phoney data akin to real data from random noise. Through adversarial training, where the generator attempts its best to fool the discriminator and the discriminator attempts its best to identify the created phoney data, the generator and the discriminator compete with one another. This procedure keeps on until the generator produces data the discriminator cannot precisely differentiate as phony data.

Usually, the training process of a GAN consists in two phases: first, the discriminator is trained with both real and generated data, with the aim of maximising the probability of recognising real data while minimising the probability of incorrectly determining the generated data as real; then, the generator starts training, with the goal of producing samples as closest to the real data as possible, so that it is indistinguishable by the discriminator. By always optimising their loss functions, the generator and the discriminator progressively raise the quality of the produced data until at last the generated data is visually exactly like the genuine data. The GAN's training process is really an adversarial game problem, in which the generator's objective is to maximise the discerning mistake rate and the discriminator's objective is to maximise the probability of properly categorising the data (Sampath et al., 2021).

Researchers have suggested several enhanced variations to solve the several issues of training instability, pattern collapse, and poor generation quality by means of GAN, therefore addressing the several difficulties experienced by the original GAN model throughout the training process. One prominent form is conditional GAN (cGAN), which introduces conditional variables (labels, images, etc.)

therefore restricting the generator's generating process (Kang and Park, 2020). This allows the generator to customise new data samples depending on criteria or needs in addition to producing them. In many useful applications, particularly in activities such image generation, picture-to-image conversion, etc., where it can create images with certain styles or features that satisfy the user's expectations, this gives cGAN a great benefit. For tasks including face generation and image style migration, for instance, cGAN can efficiently regulate the features of the produced samples to guarantee the correctness and diversity of the generated material.

Another development approach to solve the instability issue of the original GAN during the training process is Wasserstein GAN (WGAN). The Wasserstein distance can better capture the data more smoothly distribution differences than the conventional Jensen-Shannon divergence, so addressing the gradient vanishing issue during GAN training. Widely applied in tasks like image production and picture super-resolution, this approach greatly increases the stability of the generating process and lowers the pattern collapse that could develop throughout the training phase. Moreover, CycleGAN creatively introduces unsupervised learning methods to generate image-to-image conversion devoid of paired data (Hindarto and Handayani, 2024). Especially in cases when paired data is not available, such image style transformation and image creation tasks on unlabelled datasets, this function makes CycleGAN perform well in style migration and image transformation tasks.

Another crucial enhanced model is BigGAN, which, by extensive training and sophisticated model design, significantly raises the quality and resolution of the produced images. BigGAN not only solves the issue of low resolution of the images produced by the conventional GAN and unclear details, but also generates more diversified and high-quality images, which is especially remarkable in the tasks requiring the generation of high-density images. Usually trained on large-scale datasets and high-performance computing resources, BigGAN can generate high-resolution images, tasks extensively applied in the domains of complicated picture generation and art creation (Barbierato and Gatti, 2024).

StyleGAN also fits quite well for producing excellent face shots. It uses a hierarchical generator architecture, which may influence the style of several layers of the image to produce more natural and creative images. StyleGAN's architecture lets the generator independently control the structure and specifics of the image, including the background, facial traits, etc., so offering fresh technical assistance for art creativity and avatar production (Melnik et al., 2024). This layered architecture lets StyleGAN create high-quality photos while dynamically changing the style of every level of the image, hence improving the variation and realism of the created images.

GANs demonstrate immense potential in computer vision and image processing, capable of generating high-quality images for applications such as data augmentation and super-resolution reconstruction. They can also perform style transfer and image-to-image conversion, such as transforming daytime landscapes into night time scenes or converting facial images into cartoon styles. In speech synthesis, GANs can generate natural-sounding speech suitable for tasks like voice assistants. Furthermore, GANs can generate realistic training data, particularly when data is scarce. They produce samples that closely resemble real data, enabling the training of other models.

GANs still have certain difficulties in useful applications even if they have shown great generative ability in many fields. First, GAN's often erratic and prone to pattern collapse training process results in unequal produced sample quality. Second, it is still difficult to assess the quality of produced samples efficiently, particularly for some high-resolution image producing projects. Furthermore, limiting GAN's applicability in some jobs is its need on high-quality datasets. Thus, current research still revolves around how to enhance the training stability of GANs, raise the diversity of generating outputs, and implement them in a larger spectrum of fields.

3 Personalised art typography

Personalised art font design is the development of fonts with individual traits by means of distinctive design styles and aspects depending on needs, aesthetics and cultural background. Personalised design is becoming more and more sought for in the domains of brand communication, advertising creativity, social media and internet content creation as the digital age develops. Apart from providing textual information, personalised fonts can convey emotions, help to develop brand image and improve visual appeal by means of distinctive design approaches (Tian and Song, 2024). Thus, especially in web design, advertising design, product packaging, game development, and other sectors with a broad spectrum of uses, tailored font design has progressively grown to be a major section of the design profession.

Usually depending on designers' hand-made creativity or computer-aided design tools, traditional font design seeks to produce typefaces with distinctive art characteristics. This method does have several restrictions, particularly in cases with extensive customised needs when the design efficiency is poor and it is challenging to satisfy the wants of several users or scenarios. Later research has primarily depended on the rule-based approach, which sets some design rules (e.g., symmetry, proportion, line smoothness, etc.) so producing typefaces in the design space. This method does, however, have limited design freedom and is challenging to meet sophisticated customisation needs. More and more studies are striving to create typefaces with a high degree of personalisation using a data-driven method that automatically learns the art aspects and styles in font design with the arrival of machine learning (ML) and DL approaches.

Among the most often used DL techniques is convolutional neural network (CNN). CNN has a major advantage in image recognition and style migration activities since it can automatically extract features from font pictures. Researchers apply CNN for automatic classification and style analysis of font samples in personalised art font design (Lian et al., 2018). Learning the structural elements of many font samples helps CNN to automatically classify typefaces and create fonts that complement a given style. Training the CNN model, for instance, helps the system to automatically create fonts with a given style depending on the text content and user choices input. This method not only enhances design efficiency but also lets font design rapidly change the style and details depending on needs.

In the present topic of typography, style migration technique is also a common study path. Applying the style of one image to another helps style migration to separate and mix style and content. Style migration is applied in font design to move current font styles to new glyphs, therefore producing unique fonts rich in art sense that satisfy consumer expectations. Style migration balances artistry with intelligibility by allowing one to influence the visual style of a typeface and so modify its form.

Another often used DL method in typeface creation is autoencoder. The autoencoder can enable the algorithm to extract more abstract font elements from the data, therefore producing fonts that complement the input style in personalised art font design (Farahani et al., 2023). Through an encoder, autoencoder reduces high-dimensional input high-dimensional data into a low-dimensional representation; subsequently, a decoder reconstructs the output. Autoencoders therefore may learn the fundamental structure and patterns of fonts from a lot of font samples. Customised generation of typefaces can be attained by varying the latent space encoding, therefore offering users tailored font design services.

Apart from DL techniques, genetic algorithm (GA) has also found application in font design. GA imitating the natural selection process looks for the best solution in the design space. Through intersection, mutation and other operations, GA can search in font style, stroke structure and other elements to find a font design that satisfies personalised needs in the process of font development. This method is especially appropriate for situations like brand fonts and art fonts that call for extremely sophisticated and individualised design chores.

Font categorisation and creation also apply to ML techniques such decision tree (DT) and support vector machine (SVM). These systems can automatically identify the characteristics of many typefaces and create fonts that satisfy criteria depending on user input by training classifiers. SVM can be used, for instance, to classify various font styles; DT can help design systems make decisions depending on font-specific characteristics and create fonts that satisfy the user's particular requirements.

While several techniques have been applied to get specific results in customised art font creation, the sector still has many difficulties. First, one of the challenges in present study is how to guarantee that the produced typefaces possess not only great art quality but also good readability. Many generation techniques can create unique typefaces; however, they sometimes overlook font readability in useful applications (Go and Mothelsang, 2024). Second, still much to be investigated is how best to precisely realise individual needs and successfully capture the design goal using algorithms. Furthermore, the variety and art ability of fonts complicate the building and annotation of datasets; so, in this field, it is still difficult to create rich and high-quality font datasets.

The study of personalised creative font design has generally entered a fast development phase; the advent of several algorithms has made font design in this sector more efficient, adaptable, and diversified. Personalised art font design will provide more intelligent solutions for font needs in many sectors and achieve larger breakthroughs in creativity, customisation and practicality in the future as AI develops.

4 Personalised art font design model based on improved GAN

4.1 Requirement analysis

Traditional font design techniques cannot satisfy the needs for efficiency, accuracy, and diversity in font design in modern culture given the growing desire for customised and art design. Personalised art fonts are not only a key component in brand communication, advertising inventiveness and social media content production but also capable of communicating emotions, expressing cultural implications and improving visual appeal in the digital world. Consequently, in the realm of current font design, the capacity to automatically create art fonts depending on users' customised wants has grown to be a crucial necessity.

First, the tailored need for typeface design has expanded noticeably. Thanks to the extensive usage of corporate branding and internet advertising, brands and individual users are more and more motivated to adapt fonts to fit their own style depending on necessity. Without depending on professional designers to spend a lot of time on customised changes, users want to be able to fast obtain an art font design that suits their personal or brand needs in an easy method. Modern design tools and technology allow users to quickly create fonts that satisfy their needs in terms of style, thickness, decoration, and other criteria by means of automatic generation, therefore enhancing design efficiency.

Accuracy in modelling comes second. Traditional font design lacks versatile customising choices, hence, users sometimes have just to choose the current font style. Modern design depends on exact changes based on the needs of the user. Design tools must be able to comprehend user preferences and create font styles that satisfy those tastes if they are to satisfy this demand (Matyas and Kamargianni, 2019). Easy control of design elements helps the design process to be more flexible and efficient, therefore lowering manual involvement and enhancing user experience.

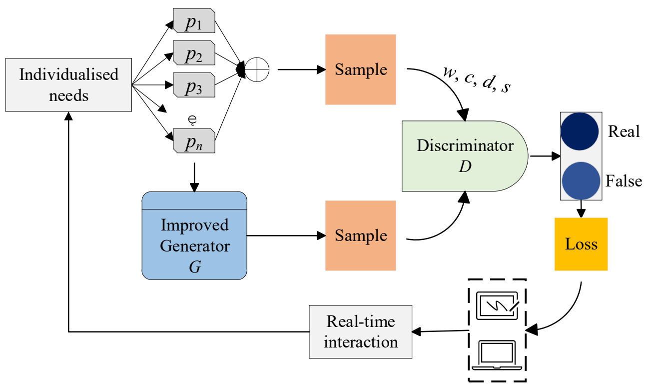
Finally, creating tailored font design depends on dynamic optimisation of the design process. While modern font design must be able to maximise depending on real-time feedback, conventional design sometimes requires designers to constantly change and alter font styles. Design tools must include a feedback system allowing user comments on produced typefaces to be accepted and instantly modified (Miller et al., 2018). This interactivity and feedback system not only increases design correctness but also helps the user to participate, therefore personalising the design process.

The main criteria of personalised art typeface design are thus: the capacity to effectively handle various and personalised needs, guarantee high quality and detailing of fonts, precisely model user preferences, dynamically optimise the design process, and have fast generation of fonts. Modern font design tools can enable users with more accurate, creative personalised font design services by satisfying these needs and so support the intelligent and automated evolution of the design process.

4.2 Model design

In this work, the StyleGANFont model effectively creates customised art fonts by creatively aggregating the enhanced methods of GAN, see Figure 1. The model consists of three basic modules, each with special purposes and goals, cooperating to encourage the application of the model in art font creation, therefore attaining efficient and accurate font design.

Figure 1 Design of StyleGANFont model (see online version for colours)



4.2.1 Personalisation requirements modelling

The fundamental module of the StyleGANFont concept is personalised requirements modelling, which seeks to create creative fonts satisfying user design needs. Practically, consumers' design needs include several dimensions including font style, line variations, decorative elements, uniqueness of font shapes and so on in addition to fundamental font thickness, size and other basic properties. Therefore, the secret to customised font production is how to convert these several design needs into input information the model can handle.

First, the model converts the user's design demands into a variable representation so that it may fairly depict her personalised needs. Specifically, setting the user's input demand as a multidimensional variable P, P can be represented as:

$$P = \left(p_1, p_2, \ldots, p_n\right) \tag{1}$$

where p_i shows the user's taste for a given design feature, such as p_1 might be the font's thickness; p_2 might be the glyph's curve; p_3 might be the font's decorativeness etc. Then these inputs are standardised using a formula to get the normalised variable P_{norm}:

$$P_{\text{norm}} = \frac{P - \mu}{\sigma} \tag{2}$$

where correspondingly μ and σ are the mean and standard deviation of the design elements. Standardised variable P_{norm} guarantees that all design aspects are handled at the same scale, therefore preventing the negative consequences of varied scales on model training. By means of this method, the design needs of the user can be effectively expressed as a multidimensional standardised variable, therefore offering a consistent basis of input for the next generation phase.

Next, the model uses a deep neural network to handle the tailored needs. In particular, the user's demand variable P_{norm} is weighted and combined with the generator's parameters to generate a weight variable W that shows the link between the user's requirements and the font design elements. The model understands the mapping link between every design element and the final font (Kasurinen and Knutas, 2018). We modify the weight variable by optimising the objective function so that the produced typefaces can be as close as feasible to the user's specific requirements; the expression of the optimisation objective function is:

$$L(W) = \sum_{i=1}^{m} \left(W_i \cdot P_{\text{norm}} - G_i\right)^2 \tag{3}$$

where G_i indicates the genuine features of the typefaces produced by the model; m is the dimension of the design components; W_i is the coefficients of the related elements in the weight variables; $L(W)$ is the model's loss function. Reducing the loss function helps the model to maximise the weight variable W so that the produced fonts satisfy the user's customised needs on style, thickness, and glyph variation.

Apart from the design criteria given by the user, the module for tailored requirements modelling has to take typeface design's practicality and aesthetics into account. Thus, in the model, we add further restrictions and auxiliary objectives to guarantee that the produced fonts not only satisfy the users' particular needs but also have good readability and artistry in pragmatic applications. One can convey this constraint mechanism by means of the following optimisation goals:

$$L_{total}(W) = L(W) + \lambda \cdot L_{constraint}(W) \tag{4}$$

where λ is a hyperparameter controlling the weights and $L_{constraint}(W)$ is a loss function reflecting restrictions including aesthetics and readability. While following individualised requests, the model can retain the readability and attractiveness of fonts by means of this objective function.

Furthermore, the module on personalised demand modelling facilitates, via a feedback system, ongoing refining and adjustment of the user demand model. Early on in generation, users could have to adjust fonts and submit fresh comments. By means of an online learning paradigm, these inputs shape the updating of the model therefore facilitating the more precise capture of changes in user needs (Pérez-Sánchez et al., 2018). This approach enhances the dynamic adaptability of the model even more, therefore producing typefaces more sensitive to users' real-time requirements.

By using the foregoing method, the personalised requirements modelling module effectively captures and models the design needs of the user, therefore offering sufficient support for next typeface development. This procedure not only increases design adaptability but also offers strong technical assurance for art font customisation.

4.2.2 Font generation and optimisation

The fundamental component of the StyleGANFont model is the font generation and optimisation module, which uses the optimisation mechanism to improve the quality, stability and artistry of the fonts created. This module uses enhanced GAN-based generating architecture to guarantee that the produced fonts not only satisfy the customised needs but also have good readability and visual impacts.

This module uses latent variables z to create fonts that satisfy design criteria once the generator G of the modified GAN gets personalised variables from the user (e.g. font thickness w, glyph curvature c, decorativeness d, and letter spacing s). Specifically, assuming the user enters personalised criteria w, c, d, s, the generator constructs a target font $\hat{F}$ by acting on these design requirements with latent variables z in a latent space Z. One can graph this procedure as follows:

$$\hat{F} = G(z, w, c, d, s) \tag{5}$$

where G is the enhanced generator; z is the latent variable; w, c, d, s are the user-entered personalised design criteria. This allows the generator to dynamically change the properties of the produced typefaces in response to the several needs expressed by the user. This equation corresponds to Step 2 of the simulation process: the latent vector is output as a candidate font image by generator G.

Apart from fulfilling personalising requirements, the design of creative fonts depends critically on the aesthetics of the font, the line smoothness, and the harmony of the glyphs (Al-Adilee, 2024). Thus, an optimisation technique is implemented to guarantee that the produced fonts not only satisfy the user's needs but also have good visual artistry and readability.

The optimisation technique introduces a discriminator D to assess the quality of the produced font $\hat{F}$. The discriminator's job is to assess the fonts generated against the actual ones by finding their differences. Based on discerning feedback from discriminator D, generator G maximises produced fonts. The aim is to get the produced fonts closer to the actual typefaces so enhancing the quality and creative feeling of the produced works. One may express the model's optimisation goal as:

$$L_G = \mathbb{E}_z\left[\log\left(1 - D\left(\hat{F}\right)\right)\right] \tag{6}$$

$$L_D = \mathbb{E}_x\left[\log D(x)\right] + \mathbb{E}_z\left[\log\left(1 - D\left(\hat{F}\right)\right)\right] \tag{7}$$

where $D(x)$ signifies the probability of the discriminator's judgement on the real font x; $D(\hat{F})$ denotes the probability of the discriminator's judgement on the generated font $\hat{F}$; ; L_G and L_D are respectively the loss functions of the generator and discriminator respectively. While the discriminator maximises the L_D to better separate the created fonts from the original fonts, the generator enhances the quality of font generating by decreasing the L_G.

Furthermore, included in the optimisation process is an adaptive training mechanism that may instantly modify the training plan based on user comments and font quality produced. For instance, the model would dynamically change the generator's settings to more precisely create fonts that meet user needs on design aspects should the produced fonts fall short (Wang et al., 2020). The adaptive mechanism has mathematical form:

$$G_{new} = G_{old} + \alpha \cdot \nabla L_G \tag{8}$$

where G_{new} is the optimised generator; G_{old} is the old generator; α = 0.0002 is the learning rate; ∇L_G is the gradient of the loss function over the generator settings. By means of this optimisation approach, the generator can be regularly changed in response to user comments and needs, therefore progressively raising the compliance and quality of the produced typefaces.

Combining the enhanced GAN architecture with the adversarial training of the generator and the discriminator, as well as the adaptive optimisation mechanism, guarantees that the font generating and optimising module ensures that the model is able to generate fonts that meet personalised needs and are of high quality and art by means of which Apart from enhancing the adaptability and variety of font design, this module guarantees the stability and effectiveness of the generating process.

4.2.3 Real-time interactions and feedback

An integral component of the StyleGANFont concept, this module helps to improve the user experience and hence the efficacy of tailored design. It enables the user to real-time modify the font design settings in response to input, so optimising them to guarantee that the produced fonts more meet user needs and aesthetics. This module not only raises system interactivity but also significantly increases personalised design's correctness and versatility.

The real-time interaction and feedback module also combines a dynamic feedback system to enable the accuracy and efficiency of the interaction between the user and the model. The model will modify the generating approach based on user feedback whenever the user assesses the produced typefaces to better fulfil user needs in the next generation phase (Bilgram and Laarmann, 2023). User comments are especially measured using a ranking system. These ratings will be used as new tuning factors to affect the font generating process. The process's mathematical formula is:

$$P_{adjusted} = P + \lambda \cdot \left(f_w, f_c, f_d, f_s \right) \tag{9}$$

where P is the personalised design parameter; $\lambda = 0.1$ is the feedback adjustment factor; f_w, f_c, f_d, f_s are user feedback scores for thickness, curvature, decorateness and letter spacing. By means of this technique, the model converts the real-time feedback of the user into design parameter adjustments, so enhancing the match and satisfaction of the produced typefaces. After each training round, the real-time interaction module feeds back the user rating λ to the generator, which then adaptively adjusts the weights according to formula (8), achieving closed-loop simulation optimisation.

Real-time feedback optimisation covers quality evaluation based on produced typefaces in addition to direct user ratings. The system might, for instance, include a built-in font quality rating mechanism to automatically grade produced typefaces. As extra feedback to help the model be optimised, this evaluation model would grade the typefaces depending on their appearance, readability, artistry, etc. (Lee et al., 2023). Without thorough design knowledge, this automatic scoring method will enable users to evaluate the quality of the produced fonts fast and make efficient changes.

Font score S of the evaluation model can be weighed and computed depending on certain design elements to make the feedback mechanism more intelligent. The computation technique is:

$$S = w_r \cdot r + w_a \cdot a + w_s \cdot s \tag{10}$$

where w_r, w_a, w_s are the weights of the relevant attributes; r, a, s are the readability, artistry, and stylistic consistency ratings of the typefaces accordingly. The model will be guided to maximise the generating process using the final font score S as feedback input.

Furthermore, supported by the real-time interaction module are several kinds of feedback. Simple interactions like sliders, buttons or input boxes let users change the font's design settings. These interactions guarantee that even non-professional designers may quickly engage in the font design process. By means of this easy interaction, users can customise fonts based on their own requirements and aesthetic criteria, therefore producing fonts with distinctive design.

In essence, the real-time interaction and feedback module introduces a dynamic feedback mechanism and an automatic quality evaluation system, improving the generation process and making the user interface more intelligent and precise, so supporting real-time adjustments and fast feedback. While the produced fonts can be more in line with the requirements of customised design, so achieving efficient and accurate personalised creative font design; the user's experience of involvement and interaction is much strengthened.

5 Experiments and results analysis

5.1 Data sets

This paper selects the Google Fonts dataset, a free font database extensively used in the world, covering a rich variety of font types and styles, and is widely used in the fields of web design, graphic design, font development and academic research, so verifying the validity of the proposed personalised art font design model. The dataset is not only rich in quantity, including several languages and design styles, but also totally free, supporting both personal and commercial use, which is rather useful as a basic dataset for font generating research.

Google Fonts spans a broad spectrum of font types, including serif, sans-serif, handwritten, and decorative fonts; some fonts have varying thickness, width, and skew variants, therefore enabling easy simulation of diverse personalised needs. Apart from English, which has high cross-language scalability, the dataset covers several languages including some Chinese, Korean, Japanese, Arabic and other characters.

Table 1 Details from Google Fonts dataset

Dataset name	*Google fonts*
Languages covered	English, Chinese (partial), Arabic, Japanese, Korean, etc.
Font categories	Serif, sans-serif, handwriting, display, decorative
Example fonts	Roboto, open sans, noto serif, pacifico, lobster
Available styles	Thin, regular, bold, italic, bold italic, etc.
Application areas	Web design, mobile apps, print design, academic research
Data format	.ttf, .otf, .woff, .woff2

This paper focuses on choosing a subset of fonts that have clear style characteristics and rich design details based on the actual research needs and performs the required screening and annotation on the font samples to guarantee that the model can create high-quality art fonts stably under the conditions of personalised demands. Table 1 contains Google Fonts dataset specifics.

This curated font subset is released under the SIL open font license (OFL). By using the aforesaid dataset, together with the collation of font style labels and the extraction of personalised parameters, the model in this article can efficiently learn various style aspects based on rich fonts, so realising high-quality art fonts generation for personalised demands.

5.2 *Experimental setup*

This work uses a set of optimum experimental settings to validate the efficiency of the proposed personalised art font design model StyleGANFont during the training process. Initially, the learning rate was set using an exponential decay approach to 0.00020.00020.0002. While in the latter phases the model can make careful modifications at a smaller speed, this approach guarantees that the model can converge fast in the early stages of training, therefore avoiding overfitting and boosting the stability of the model.

About the batch size, this work chooses 64, a value that strikes a compromise between memory management and computing economy. While keeping enough sample diversity to guarantee the computational efficiency of every iteration, a reduced batch size can help to lower the memory load. Every batch of training guarantees adequate samples of various fonts so the model may understand the diversity and complexity of fonts more effectively. The initial value was 2×10^{-4}.

This work uses the Adam optimiser with hyperparameters $\beta_1 = 0.9$ and $\beta_2 = 0.999$ in the choice of optimisation methods to efficiently prevent the phenomena of gradient explosion or disappearance by means of dynamic alteration of the gradient. The model's training process is thus steadier and can rapidly converge with an ideal solution. Widely validated and especially fit for the training of generative models is the Adam optimiser.

Finally, one highlight of this work is also the design of the loss function. This work combines adversarial loss and content loss in GAN to guarantee that the produced typefaces preserve the details and art integrity in addition to enough realism. The model is validated every 20 rounds during the training process; there are thus set to be 200 total training cycles. Every experiment ran on servers with NVIDIA Tesla V100 GPUs to provide effective computing capability and training capacity.

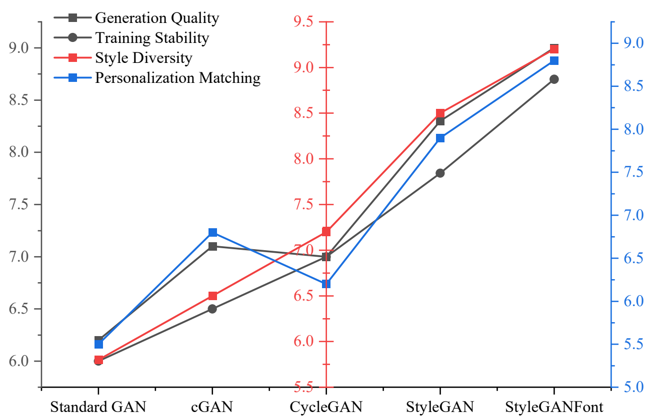
5.3 *Experimental procedure*

This work intends to validate the efficiency of the StyleGANFont model by two sets of tests. The first group evaluates the improvement in font generating quality and personalising performance of the model by means of a comparative experiment with the conventional model. The second group is an ablation experiment meant to investigate every module's contribution to the general effect. The performance benefits and main design roles of the model are fully shown by means of these two sets of tests. Four representative generation models, traditional standard GAN, cGAN, CycleGAN and StyleGAN, are chosen as comparison objects in Experiment 1, to verify the advantages of StyleGANFont in the task of personalised art font generation. variations in the capacities for quality and personalisation.

The traditional representative of generative models, Standard GAN, suffers from inconsistent training and pattern collapse yet has a straightforward structure. Conditional information introduced by cGAN improves the controllability of generated samples, appropriate for creating tasks with certain styles or qualities. Suitable for style migration and cross-domain font production, cycleGAN achieves style transformation using unsupervised learning. High-quality generative effects and hierarchical style control of styleGAN are well-known traits. is extensively applied in high-resolution picture production and yields control and high-quality generation.

In this experiment, the above four models and the StyleGANFont proposed in this paper are trained under the same dataset and training conditions, and the performance differences of the models are comprehensively compared by evaluating the four indexes, namely, the generating quality, the style diversity, the personalised matching degree and the training stability, so verifying the superiority of StyleGANFont. Figure 2 shows the experimental outcomes.

Figure 2 Results of the comparison experiment (see online version for colours)



With a score of 9.0, StyleGANFont leads in terms of generating quality, much above both cGAN (7.1) and the conventional Standard GAN (6.2). Standard GAN has a quite basic structure, which makes it challenging to capture the intricate nuances of typefaces, hence producing blurriness of fonts and a lack of creativity. Through the insertion of conditional information, cGAN enhances the control and detail of the produced typefaces; yet it lacks in depth of detail. still lacks richness in detail but increases the controllability and detail performance of generation. By means of multi-level style control and optimisation techniques, StyleGANFont exhibits superior capacity to sustain font clarity and detail performance.

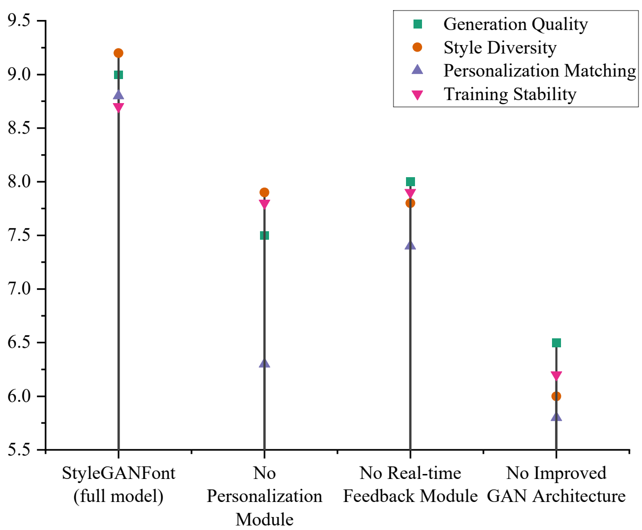
StyleGANFont earns the highest 9.2 points out of all the styles, followed by CycleGAN with 7.2 points and StyleGAN with 8.5 points. CycleGAN can accomplish a certain degree of style variation and is good at unsupervised style transformation; nevertheless, because direct modelling of tailored requirements is lacking, its style control is somewhat limited. StyleGAN shines at hierarchical style management; yet, by adding the customised demand modelling module, which may produce richer and more varied font styles, StyleGANFont extends the area for style expression.

StyleGANFont dominates the comparison models in the examination of personalisation with an 8.8 score, especially more than Standard GAN with a score of 5.5 and CycleGAN with a score of 6.2. With a score of 6.8, cGAN has limited power of personalisation even if it can create styles depending on conditional variables. StyleGANFont uses a real-time interaction approach and a user preference learning module to reach this. Learning module and real-time interaction mechanism greatly enhances the customised matching impact of typefaces and responds precisely to user input needs.

StyleGANFont also demonstrates a great advantage in terms of training stability; it gets an 8.7. Though rating only 6.0 and 6.5 respectively, traditional GAN and cGAN are prone to instability and pattern collapse during training. With cyclical consistency loss, cycleGAN reduces part of the instability; its score is 7.0. StyleGANFont enables continuous model optimisation and high quality of model generation by combining the adaptive training mechanism, which essentially enhances the stability of the training and the speed of convergence.

Experiment 1 essentially confirms in terms of font generating quality, style diversity, personalisation matching and training stability the great advantages of StyleGANFont. This work develops the ablation experiment to thoroughly grasp the contribution of every important module in the StyleGANFont model to the font generating impact. The effect of every module on the general generating quality, style diversity and personalisation matching is assessed by progressively eliminating or substituting the fundamental sections of the model and tracking the changes in model performance.

Figure 3 Results of ablation experiments (see online version for colours)



First, the model will not be able to faithfully represent and react to the user's preferences by eliminating the personalisation modelling module, hence not adjusting the creation process to the personalisation needs entered by the user. This environment makes it possible to assess how this module affects user happiness and tailored matching of produced typefaces. The real-time interaction and feedback module was then deleted, therefore removing the mechanism for real-time optimisation depending on user feedback during model training. This configuration seeks to confirm how real-time interaction affects user involvement, generation quality, and training stability. Finally, the Improved GAN Architecture module is deleted, and the improved GAN architecture replaces the conventional GAN architecture to validate the contribution of the improved GAN architecture in terms of detail control, stability, and stylistic diversity of produced typefaces. Figure 3 shows the outcomes of every ablation experiment.

With a score of 9.0, the StyleGANFont model excels among all the experimental configurations in terms of Generation Quality, therefore displaying the strength of the model in terms of detailed performance and general quality. Eliminating the personalisation requirements modelling module reduces the generating quality to 7.5, suggesting that personalisation modelling has a major influence on it. The generation quality somewhat drops to 8.0 points once the real-time feedback module is removed, indicating that the model still preserves a good generating effect; yet there is no mechanism for timely feedback, so the details are somewhat insufficient. The capacity of the model to regulate details and generation quality is clearly compromised when the enhanced GAN architecture is removed, so the generation quality decreases dramatically to 6.5 points. This indicates that the improved GAN architecture is hence very important in generating impact.

With a score of 9.2, StyleGANFont keeps leading in terms of style variety since it shows that the model can produce a wide spectrum of font styles. Eliminating the style control module results in a drop in style variety to 7.9 and less varied and varied generated fonts, thereby demonstrating that style control is vital for creating different fonts. The style diversity falls somewhat to 7.8 without the real-time feedback module, although the impact is minor and some degree of style variation can still be produced. Reflecting the significant contribution of GAN architecture optimisation on style variety, the style diversity declines to 6.0 and the richness of font styles is drastically constrained after eliminating the enhanced GAN design.

Regarding personalisation matching, the elimination of the personalisation requirements modelling module drastically lowers the matching score to 6.3, therefore suggesting that the module is important in producing typefaces that satisfy the needs of the user. Other parameters have less influence. The personalisation matching score declines to 7.4 and 5.8 respectively after eliminating the real-time feedback module and the upgraded GAN architecture; yet the impact is somewhat little when compared to the removal of the personalisation requirements modelling module. The matching score stays high at 7.9 when the style control module is taken out, suggesting that, to some degree, the variety of styles can still satisfy personalising needs.

StyleGANFont boasts the best training stability, a score of 8.7. The training stability is 7.9 once the real-time feedback module is taken out, this is a minor decline but still retains good stability. Following the removal of the personalised demand modelling module and the enhanced GAN architecture, the training stability falls to 7.8 and 6.2 respectively, clearly indicating that these two modules are essential for raising the stability and convergence speed during training.

The impact of every module of StyleGANFont on generating quality, style diversity, personalisation matching and training stability is demonstrated above. Particularly important for the general performance of the model are the personalisation requirements modelling module and the upgraded GAN architecture; however, deleting these modules causes a notable performance loss. This confirms even more the relevance of every module in the architecture of the model and offers a foundation for later model improvement.

6 Conclusions

This work suggests a customised art font design approach grounded on enhanced StyleGANFont. Comparative analysis of several conventional generating models reveals that StyleGANFont has notable benefits over other conventional font generating algorithms. Especially in enhancing the customised matching degree and style variety, which plays a major influence, the ablation studies highlight the relevance of important modules such personalised demand modelling, style control, real-time interaction and feedback on the generating effect. Concurrently, the enhanced control of generation details and training stability depends much on the better GAN architecture.

There are still some restrictions even if the StyleGANFont model performs quite well on some measures. First, especially when creating high-resolution typefaces with more training time and memory consumption, which may restrict its applicability in resource-constrained surroundings, the training process of the model is more demanding in terms of computational resources. Second, even if tailored requirements modelling enhances font generation's adaptability, present models still fall short in adequately expressing complicated design needs of users. Finally, present models mostly depend on stationary datasets; so, more research on how to employ dynamic user data for more accurate customised design is still necessary.

Future studies can maximise and extend the StyleGANFont model in several respects:

1 Improve model training efficiency: Future studies should concentrate on optimising the model architecture and training algorithms, so lowering training time and memory consumption by using more effective training strategies, and so increasing model usability in situations with limited resources.

2 Enhancing personalised demand modelling capabilities: Future studies could expand the kinds of user inputs to improve the capacity of the model to adapt to various inputs and demanding design criteria. Combining dynamic inputs or richer user behaviour data, for instance, can help the model produce more personally tailored accuracy and font variation.

3 Real-time feedback and online learning: Online learning technologies can be integrated with this approach to provide constant learning and optimisation based on user comments in useful apps. Dynamic updating the model parameters and optimisation procedures helps the produced typefaces to be more fit for the evolving needs of consumers, therefore offering more accurate and individualised design services.

4 Multimodal input and generation: Future studies can investigate the mix of multimodal inputs, for example, by means of text descriptions, voice instructions or drawing inputs, so enhancing the model's capacity to grasp and create several kinds of creative expressions. This allows not just the creation of fonts with more vivid visual effects but also the expansion of user engagement methods.

StyleGANFont will be more equipped to satisfy the ever more complicated needs of individualised design and play a bigger part in the creative sectors by means of these optimisations and developments.

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Declarations

All authors declare that they have no conflicts of interest.

References

Al-Adilee, S.M.S. (2024) 'Designing visual symbols in digital culture', *American Journal of Social Sciences and Humanity Research*, Vol. 4, No. 8, pp.244–271.

Barbierato, E. and Gatti, A. (2024) 'Toward green AI: a methodological survey of the scientific literature', *IEEE Access*, Vol. 12, pp.23989–24013.

Bilgram, V. and Laarmann, F. (2023) 'Accelerating innovation with generative AI: AI-augmented digital prototyping and innovation methods', *IEEE Engineering Management Review*, Vol. 51, No. 2, pp.18–25.

Farahani, A.M., Adibi, P., Ehsani, M.S., Hutter, H-P. and Darvishy, A. (2023) 'Automatic chart understanding: a review', *IEEE Access*, Vol. 11, pp.76202–76221.

Go, E.M. and Mothelsang, K. (2024) 'Trends in modern typography design: visual preferences on e-commerce platforms', *International Journal of Graphic Design*, Vol. 2, No. 2, pp.248–263.

Günay, M. (2024) 'The impact of typography in graphic design', *International Journal of Eurasia Social Sciences*, Vol. 15, No. 57, pp.1446–1464.

Habeeb, D., Alhassani, A., Abdullah, L.N., Der, C.S. and Alasadi, L.K.Q. (2024) 'Advancements and challenges: a comprehensive review of GAN-based models for the mitigation of small dataset and texture sticking issues in fake license plate recognition', *Engineering, Technology & Applied Science Research*, Vol. 14, No. 6, pp.18401–18408.

Hindarto, D. and Handayani, E.T.E. (2024) 'Revolution in Image data collection: CycleGAN as a dataset generator', *Sinkron: Jurnal Dan Penelitian Teknik Informatika*, Vol. 8, No. 1, pp.444–454.

Kang, M. and Park, J. (2020) 'Contragan: contrastive learning for conditional image generation', *Advances in Neural Information Processing Systems*, Vol. 33, pp.21357–21369.

Kasurinen, J. and Knutas, A. (2018) 'Publication trends in gamification: a systematic mapping study', *Computer Science Review*, Vol. 27, pp.33–44.

Lee, T., Yasunaga, M., Meng, C., Mai, Y., Park, J.S., Gupta, A., Zhang, Y., Narayanan, D., Teufel, H. and Bellagente, M. (2023) 'Holistic evaluation of text-to-image models', *Advances in Neural Information Processing Systems*, Vol. 36, pp.69981–70011.

Lian, Z., Zhao, B., Chen, X. and Xiao, J. (2018) 'EasyFont: a style learning-based system to easily build your large-scale handwriting fonts', *ACM Transactions on Graphics (TOG)*, Vol. 38, No. 1, pp.1–18.

Matyas, M. and Kamargianni, M. (2019) 'Survey design for exploring demand for mobility as a service plans', *Transportation*, Vol. 46, No. 5, pp.1525–1558.

Melnik, A., Miasayedzenkau, M., Makaravets, D., Pirshtuk, D., Akbulut, E., Holzmann, D., Renusch, T., Reichert, G. and Ritter, H. (2024) 'Face generation and editing with stylegan: a survey', *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 46, No. 5, pp.3557–3576.

Miller, K., Mosby, D., Capan, M., Kowalski, R., Ratwani, R., Noaiseh, Y., Kraft, R., Schwartz, S., Weintraub, W.S. and Arnold, R. (2018) 'Interface, information, interaction: a narrative review of design and functional requirements for clinical decision support', *Journal of the American Medical Informatics Association*, Vol. 25, No. 5, pp.585–592.

Pérez-Sánchez, B., Fontenla-Romero, O. and Guijarro-Berdiñas, B. (2018) 'A review of adaptive online learning for artificial neural networks', *Artificial Intelligence Review*, Vol. 49, pp.281–299.

Purwono, P., Wulandari, A.N.E., Ma'arif, A. and Salah, W.A. (2025) 'Understanding generative adversarial networks (GANs): a review', *Control Systems and Optimization Letters*, Vol. 3, No. 1, pp.36–45.

Sampath, V., Maurtua, I., Aguilar Martin, J.J. and Gutierrez, A. (2021) 'A survey on generative adversarial networks for imbalance problems in computer vision tasks', *Journal of Big Data*, Vol. 8, pp.1–59.

Tian, Y. and Song, X. (2024) 'Emotional expression and brand identity in library logo design exploration and practice in a historical context', *Herança*, Vol. 7, No. 2, pp.112–124.

Tofail, S.A., Koumoulos, E.P., Bandyopadhyay, A., Bose, S., O'Donoghue, L. and Charitidis, C. (2018) 'Additive manufacturing: scientific and technological challenges, market uptake and opportunities', *Materials Today*, Vol. 21, No. 1, pp.22–37.

Wang, Y., Gao, Y. and Lian, Z. (2020) 'Attribute2font: creating fonts you want from attributes', *ACM Transactions on Graphics (TOG)*, Vol. 39, No. 4, pp.69: 1–69: 15.

Xiao, S., Huang, S., Lin, Y., Ye, Y. and Zeng, W. (2023) 'Let the chart spark: Embedding semantic context into chart with text-to-image generative model', *IEEE Transactions on Visualization and Computer Graphics*, Vol. 30, No. 1, pp.284–294.