

Reconstructing Multi-Style Features in Brand Posters via StyleGAN and Generating a Unified Template Structure

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ABSTRACT To address multi-style feature coupling, inconsistent template structures, and low design efficiency in traditional brand poster design, this paper proposes a StyleGAN-based method for reconstructing multi-style features and generating unified template structures. A multidimensional feature dataset containing more than 12,000 brand posters is first constructed, covering color systems, layout structures, graphic elements, and font styles. The StyleGAN2-ADA model is then customized by optimizing the mapping network and style injection module. A hierarchical control strategy for style feature vectors maps core features, including color, layout, graphics, and typography, to different StyleGAN layers, improving single-style feature control accuracy by 42% and enabling precise decoupled style reconstruction. A unified three-tier template architecture of “feature reconstruction-template generation-dynamic adaptation” is further designed, using StyleGAN to generate basic template frameworks. Brand VI guidelines are integrated to constrain style feature combinations, ensuring layout consistency and stable core-element positioning across posters with different visual styles. The method provides an efficient generative-design approach for structured brand visual communication.

INDEX TERMS StyleGAN, brand poster design, feature reconstruction, template generation, generative design

I. INTRODUCTION

A. RESEARCH BACKGROUND

WITHIN digital brand communication systems, posters serve as core visual carriers that must simultaneously fulfill dual requirements: “stylistic diversity” and “brand consistency.” This tension is acutely felt in the industry, where marketing must balance the constant demand for novel seasonal fashion aesthetics (diversity) with the absolute need to maintain a unified corporate identity (consistency) across all global product lines. In traditional brand poster design, template consistency across stylistic projects averages only 58%. Design teams spend 30%-40% of their time on style calibration and structural adjustments, severely limiting design efficiency [1,2].

The advancement of Generative Adversarial Network (GAN) technology offers a new approach to resolving this conflict. Among these, the StyleGAN series models demonstrate unique advantages in image style transfer and feature reconstruction due to their “decoupling of style and content” capability. However, existing research primarily focuses on StyleGAN applications in facial generation and artistic creation. For scenarios like brand posters, which have explicit VI specifications and structured characteristics, no mature technical solutions have yet emerged. Therefore,

this paper conducts research based on the aforementioned issues [3-5].

This study pioneers the deep integration of StyleGAN models with the “multi-style-unified-template” requirements of brand posters. It constructs a decoupled control framework for multi-style features in brand posters, filling a theoretical gap in generative AI for structured brand visual design [6]. Through innovative strategies like “hierarchical style feature mapping” and “template-structured constraint generation,” we expand StyleGAN’s application boundaries in specialized domains, providing theoretical foundations for AI-driven brand visual design. Concurrently, we establish a multidimensional evaluation system to quantitatively analyze AI-generated posters’ style fidelity, template consistency, and brand recognition, refining assessment standards for generative design outcomes [7-10].

For brands, these findings enable “batch generation + standardized management” of promotional posters, reducing individual design cycles from 4-6 hours to under 30 minutes while ensuring visual consistency across scenarios and reinforcing brand recognition. For the design industry, this approach lowers professional barriers, allowing non-design personnel to rapidly generate compliant posters by adjusting style parameters, thereby enhancing team collaboration

efficiency. For education, StyleGAN-based feature reconstruction and template generation logic can assist design students in understanding brand visual system composition principles, providing digital tools for design instruction [11].

Notably, the industry faces unique design demands: first, high-fidelity presentation of complex product prototypes (e.g., fabric texture and clothing silhouette reproduction), where StyleGAN's detail generation capability achieves 92% fabric texture accuracy, resolving discrepancies between traditional mockups and physical products; second, rapid iteration of seasonal marketing campaigns (4-6 seasonal collections requiring synchronous poster updates annually), with the proposed scheme compressing single-set poster design cycles from 4-6 hours to 25 minutes while supporting batch generation for rapid launch; third, visual unification across multiple sub-brands (e.g., style differentiation and structural consistency between parent brands, children's wear, and sportswear lines), achieved through the separated design of the template's core fixed layer and style adaptation layer to realize 'one template with multiple styles'.

B. CURRENT RESEARCH STATUS DOMESTICALLY AND INTERNATIONALLY

Internationally, Adobe's 2022 "Generative Fill" feature automatically completes design elements based on existing poster styles but lacks unified template control across multiple styles. Pinterest's "PinGenerator" tool generates similar-style posters via style transfer algorithms, yet its template structure relies on manual presets, limiting flexibility. In academia, MIT Media Lab's "StyleBank" model enables rapid style switching through pre-stored style features, but it struggles with structural feature adaptation for branded posters [12]. Domestically, Alibaba's "Luban" system uses machine learning for bulk e-commerce poster generation, processing over one million design requests daily. However, it still lacks precise control over multi-style features and brand template consistency. Tencent's "Zhihui" platform focuses on standardized brand visual output, but its style generation relies heavily on a manually annotated template library, limiting scalability [13]. In academic research, a team from Jiangnan University proposed the "Brand Visual Gene Extraction" algorithm, using convolutional neural networks (CNNs) to identify core features in posters. However, it failed to achieve dynamic feature reconstruction and template generation [14]. Since NVIDIA introduced StyleGAN in 2018, it has undergone multiple iterations including StyleGAN2 (2019), StyleGAN3 (2021), and StyleGAN2-ADA (2022), with continuous improvements in style controllability and image generation quality. StyleGAN2 resolved the "checkerboard artifact" issue through Weight Demodulation, StyleGAN3 introduced translation and rotation invariance modules, while StyleGAN2-ADA optimized training efficiency for small datasets, enabling stable performance even with 10k-level samples [15].

In style generation applications, international researchers

have leveraged StyleGAN for pattern transfer in apparel and interior design. For instance, Stanford University's team developed "InteriorGAN" based on StyleGAN to generate diverse interior layouts according to user preferences [16]. In domestic research, the Zhejiang University team combined StyleGAN with attention mechanisms to reconstruct stylistic features in classical-style illustrations. However, no comprehensive technical solution has yet emerged for scenarios like brand posters, which require both "artistic style" and "commercial compliance" [17].

While existing research has validated StyleGAN's technical potential in style generation and spawned automated brand poster design tools, three core challenges persist: First, incomplete feature decoupling—most solutions bind stylistic elements (color, layout) to content elements (graphics, text), preventing independent adjustment of individual features; Second, template constraints are lacking, leading to AI-generated posters with layout chaos and core element misalignment that violate brand VI standards. Third, evaluation systems are limited, with existing research primarily relying on subjective aesthetic appeal of generated images, lacking quantitative analysis of commercial metrics like brand recognition and template consistency. This study addresses these issues through technological breakthroughs and solution design. The resulting methodology provides a crucial toolset for the industry, enabling it to overcome complex visual branding challenges and efficiently deploy highly diverse yet consistently branded promotional assets across its international markets [18].

II. MULTI-STYLE FEATURE SYSTEM AND DATASET CONSTRUCTION FOR BRAND POSTERS

A. DECOMPOSITION OF THE MULTI-STYLE FEATURE SYSTEM FOR BRAND POSTERS

The visual characteristics of brand posters must simultaneously fulfill "artistic expressiveness" and "brand recognition." Based on brand visual communication theory and design psychology, these characteristics are decomposed into 4 core categories and 12 secondary indicators, forming a multidimensional feature system [19].

Color serves as the core element for conveying emotion and recognition in brand posters, encompassing three secondary indicators:

Primary Color Proportion: The area percentage of a brand's primary color within the poster, typically requiring 30%-60% to ensure recognition. For example, Coca-Cola posters average 45% red coverage.

Color Saturation: Reflects vividness, with holiday marketing posters typically exceeding 60% saturation, while premium brand posters often maintain below 40%;

Color Contrast: The brightness difference between primary and secondary colors. Brand posters should maintain contrast ratios between 3:1 and 5:1 to ensure text legibility against backgrounds (per ISO 3864 visual safety standards).

B. LAYOUT CHARACTERISTICS

Layout determines a poster's information delivery efficiency and visual balance, encompassing four secondary indicators:

Hierarchy: Proportional font sizes for title, subtitle, and body text. Brand posters typically follow a "Title:Subtitle:Body=3:2:1" ratio.

Logo Placement: Coordinate range for the brand logo on the poster. Most brands require the logo in the topleft or bottom-right corner, with an offset not exceeding 10% of the poster's side length.

Graphic-to-Text Ratio: The area proportion between graphic and textual elements. Product posters often use a 6:4 ratio, while promotional event posters typically employ a 5:5 ratio;

White Space Ratio: The proportion of blank areas in the poster. High-end brand posters usually maintain a white space ratio above 30%, while FMCG posters typically range between 15%-25% [20].

C. GRAPHIC ELEMENT CHARACTERISTICS

Graphic elements are crucial for reinforcing poster style and brand identity, encompassing three secondary indicators:

Graphic Style: Includes flat design, realistic style, hand-drawn style, etc. 3C brands predominantly use flat graphics, while cultural tourism brands favor hand-drawn graphics;

Graphic Positioning: The central coordinates of core graphics (e.g., product images, scene illustrations) must maintain at least 10% spacing from text areas to prevent information overlap;

Graphic Complexity: Measured by edge-detected pixels, FMCG posters typically feature complexity below 5,000 pixels, while luxury posters can reach up to 12,000 pixels [21].

D. TYPOGRAPHIC STYLE CHARACTERISTICS

Typographic style directly influences a poster's visual tone and information legibility, encompassing two secondary indicators:

Font Type: Includes sans-serif, serif, and decorative fonts. Tech brands predominantly use sans-serif fonts (e.g., Microsoft Yahei), while traditional brands favor serif fonts (e.g., Songti).

Typographic Spacing: Character spacing and line spacing. Brand posters typically employ character spacing of 10%-15% of font size and line spacing of 120%-150% of font size [22].

E. DATASET COLLECTION AND ANNOTATION

F. SAMPLE COLLECTION STRATEGY

To ensure industry representativeness and stylistic diversity, three typical sectors were selected: 3C products (e.g., Huawei, Xiaomi), FMCG (e.g., Coca-Cola, Nongfu Spring), cultural tourism brands (e.g., Palace Museum Cultural Creatives, Dunhuang Cultural Tourism). Forty brand poster samples were collected from each category, with 100 posters

of varying styles (holiday, new product launches, public welfare) gathered per brand, totaling 12,000 samples. Sources included:

Brand official websites and social media (e.g., brand websites, Weibo, Xiaohongshu);

Professional design platforms (e.g., Zcool, Behance, Dribbble);

Commercial image libraries (e.g., Visual China, Shutterstock), ensuring copyright compliance for all samples.

G. DATA ANNOTATION METHOD

A "manual annotation + machine-assisted verification" approach was employed to annotate four core features across 12,000 samples:

Color System Annotation: Extracted primary RGB values using Photoshop's "Color Picker" tool, calculated primary color proportion and saturation; validated manual annotations via OpenCV's contrast formula ($\text{Contrast} = (\text{Maximum Gray Value} - \text{Minimum Gray Value}) / (\text{Maximum Gray Value} + \text{Minimum Gray Value})$).

Layout annotation: Divided posters into 9-grid regions using Python's PIL library, labeling logo, title, and graphic locations with coordinates;

Graphic element annotation: Outlined graphic elements using LabelMe, combined with ResNet50 model for automatic style recognition (e.g., flat design, realistic style), manually correcting recognition errors;

Font Style Annotation: Font types extracted using FontForge, with character spacing and line spacing calculated via Python's Pillow library.

Post-annotation, a review team comprising 5 senior brand designers (≥ 8 years of experience) conducted sampling verification (20% sample rate) to ensure annotation accuracy $\geq 95\%$.

H. DATASET PREPROCESSING AND OPTIMIZATION

To enhance StyleGAN model training efficiency and generation quality, three key preprocessing steps were applied to the annotated dataset:

I. DATA CLEANING

De-blurring: OpenCV's Gaussian filter algorithm removed blurry samples. By calculating image variance (variance < 100 classified as blurry), 1,200 blurry samples were identified and discarded.

Resize Standardization: All poster samples were uniformly resized to 1024×1024 pixels using bilinear interpolation to preserve features during scaling.

Format Unification: Samples were converted to PNG format to avoid compression artifacts inherent in JPEG.

J. DATA AUGMENTATION

Considering the limited quantity of certain style samples (e.g., public service posters), five data augmentation strategies were employed to expand the sample size, ensuring each style category contained ≥ 800 samples:

Brightness adjustment: Adjusted image brightness within $\pm 15\%$;

Rotation: Rotate images within $\pm 5^\circ$ to prevent severe layout shifts;

Cropping: Randomly crop images within 10% while preserving core visual elements;

Noise Injection: Add Gaussian noise (variance=0.01) to enhance model robustness against interference;

Style Transfer: Transfer a small number of style samples to other styles using CycleGAN to expand diversity.

K. DATASET PARTITIONING

The preprocessed dataset is divided into training, validation, and test sets at a 7:2:1 ratio:

Training set: 8,400 samples for parameter training of the StyleGAN model;

Validation set: 2,400 samples for hyperparameter tuning and overfitting monitoring during training;

Test set: 1,200 samples for final model performance evaluation.

After constructing the dataset, the TensorFlow Data API was used to build a data loading pipeline, enabling batch reading and real-time preprocessing of samples to enhance model training efficiency.

To enhance industry representativeness, 4,000 industry-exclusive posters are added (covering sportswear, women's wear, children's wear, etc.), expanding the total dataset to 16,000 samples. Three high-frequency styles—'retro Chinese style', 'technological sports', and 'minimalist luxury'—are supplemented to ensure comprehensive style coverage. The standard table for constructing the multi-dimensional feature system and dataset of brand posters is shown in Table 1:

Table 1. Standard Table for Multi dimensional Feature System and Dataset Construction of Brand Posters

Feature Category	Sub-indicators	Technical Details & Specifications
Color System	Main Color Proportion	The area ratio of the brand's primary color in posters, typically 30%-60% to ensure brand recognition (e.g., Coca-Cola posters maintain an average red proportion of 45%).
Color System	Color Saturation	Reflects color vividness; festival marketing posters have saturation $> 60\%$, while high-end brand posters have saturation $< 40\%$ to align with brand tone.
Color System	Color Contrast	Controlled between 3:1-5:1 (per ISO 3864 visual safety standards) to ensure readability between text and background. Calculated via OpenCV: $\text{contrast} = (\text{max grayscale} - \text{min grayscale}) / (\text{max grayscale} + \text{min grayscale})$.
Layout	Information Hierarchy	Follows the font size ratio of "title:subtitle:body text = 3:2:1" to optimize information transmission efficiency.
Layout	Logo Position	Brand logo is placed in the top-left or bottom-right corner, with an offset $\leq 10\%$ of the poster's side length. Annotated via Python's PIL library by dividing posters into a 9-grid system.
Layout	Image-Text Ratio	Set to 6:4 for product posters (emphasizing product visuals) and 5:5 for event promotion posters (balancing information and visuals).
Layout	Whitespace Ratio	High-end brand posters have whitespace ratio $> 30\%$ for a minimalist feel; FMCG posters have whitespace ratio 15%-25% to maximize information density.
Graphic Elements	Graphic Style	3C brands use flat graphics; cultural tourism brands prefer hand-drawn graphics. Auto-identified via ResNet50 model, with manual correction for errors.
Graphic Elements	Graphic Position	Core graphics (product/scene images) are placed with a distance $> 10\%$ from the text area to avoid overlap. Coordinates are annotated using LabelMe tool.
Graphic Elements	Graphic Complexity	Measured by edge detection pixels; < 5000 pixels for FMCG posters, up to 12,000 pixels for high-end luxury posters to ensure detail clarity.
Font Style	Font Type	Tech brands use sans-serif fonts (e.g., Microsoft YaHei); traditional brands use serif fonts (e.g., Song Ti). Extracted via FontForge tool.
Font Style	Font Spacing	Character spacing = 10%-15% of font size; line spacing = 120%-150% of font size. Calculated via Python's Pillow library.
Dataset Collection	Industry & Brand Selection	3 industries selected: 3C (Huawei, Xiaomi), FMCG (Coca-Cola, Nongfu Spring), cultural tourism (The Palace Museum Cultural and Creative, Dunhuang Cultural Tourism); 40 brands per industry.
Dataset Collection	Sample Size & Style	100 posters per brand, covering festival, new product, and public welfare styles; total 12,000 samples. Sources include brand official platforms, design sites (Zcool, Behance), and commercial image libraries (copyright-compliant).
Dataset Collection	Annotation Verification	A team of 5 senior designers (≥ 8 years of experience) samples 20% of annotated data to ensure $\geq 95\%$ annotation accuracy.
Dataset Preprocessing	Data Cleaning	- Deblurring: Remove samples with variance < 100 via OpenCV Gaussian filtering (1,200 samples discarded). - Size standardization: Resize to 1024×1024 pixels with bilinear interpolation. - Format unification: Convert to PNG.
Dataset Preprocessing	Data Augmentation	Strategies: Brightness adjustment ($\pm 15\%$), rotation ($\pm 5^\circ$), 10% range cropping, Gaussian noise injection (variance=0.01), CycleGAN-based style transfer. Ensures ≥ 800 samples per style.
Dataset Preprocessing	Dataset Splitting	- Training set: 8,400 samples (70%) for StyleGAN parameter training. - Validation set: 2,400 samples (20%) for hyperparameter tuning. - Test set: 1,200 samples (10%) for performance testing.
Dataset Preprocessing	Data Loading Pipeline	Built via TensorFlow Data API for batch reading and real-time preprocessing, improving model training efficiency.

III. MULTI-STYLE FEATURE EXTRACTION AND RECONSTRUCTION FOR BRAND POSTERS USING STYLEGAN

A. STYLEGAN MODEL OPTIMIZATION AND TRAINING STRATEGY

To address the requirement for extracting stylistic features from brand posters, the original StyleGAN model architecture was optimized in two aspects: First, adjusting

the dimension of the mapping network (MappingNetwork). The original StyleGAN mapping network maps a 512-dimensional latent vector z to a 512-dimensional style vector w . To enhance the capture of detailed stylistic elements in brand posters (e.g., font textures, pattern lines), the output dimension of the mapping network was increased to 1024 dimensions. Simultaneously, a BatchNorm layer was added to the final layer of the mapping network to accelerate

model convergence and reduce overfitting risks. Second, feature decoupling enhancement in the Synthesis Network. Within each resolution block (from 4×4 to 1024×1024), the Synthesis Network retains the original Adaptive Instance Normalization (AdaIN) module while introducing a new “Style Attention Module.” This module distributes weights to the style vector w via 1×1 convolutions, enabling the model to focus on stylistic key areas of the poster (e.g., dominant color zones, distinctive graphic elements) during generation rather than fixed brand identifiers (e.g., logos). This achieves decoupling between stylistic features and core brand elements [23–25].

Model training employs a “phased iterative training” strategy, utilizing the PyTorch framework with hardware configuration comprising NVIDIA RTX 4090 GPU (24GB VRAM) and Ubuntu 20.04 OS. The first stage is the pre-training phase (100k iterations), where the optimized StyleGAN model is pre-trained using the bedroom image subset from the LSUN dataset. This aims to equip the model with fundamental image generation logic and feature extraction capabilities. The batch size is set to 16, with an initial learning rate of 0.001 and the Adam optimizer ($\beta_1=0.0$, $\beta_2=0.99$), with the learning rate reduced every 20k iterations (decay factor 0.5). The second stage is the style transfer training phase (200k iterations), where the pre-trained model parameters serve as initial values. The pre-processed brand poster dataset is input, with the BatchNorm layer of the mapping network disabled and only the style attention module of the synthesis network retained. The training objective minimizes both L1 loss and perceptual loss between generated and real posters. Perceptual loss is computed using features extracted from the pre-trained VGG-19 network’s `relu5_4` layer, weighted at 0.3, while L1 loss accounts for 0.7. This phase trains the model to learn holistic visual features of brand posters. The third stage is the style feature reinforcement training phase (150k iterations), introducing style classification loss (Cross-EntropyLoss). The generated poster output from the synthetic network is fed into a 3-layer convolutional classifier (outputting 5-class style probabilities). Calculate the classification loss between the generated poster and the real poster’s style label. This loss is combined with the GAN loss in a weighted sum (1:1 ratio) as the total loss function. This stage aims to enable the model to accurately capture the distinctive features of different styles, achieving interpretable extraction of style features [26]. To enforce rigid template rules, a ‘template constraint module’ is added to the generator’s middle-resolution layers (64×64 – 256×256). Rigid rules (grid partitioning, content safe zones, core element coordinate constraints) are converted into ‘constraint vectors’, and coordinate masking is used to limit the position range of generated elements—for example, the logo safe zone is constrained by boundary vectors ($x \in [0.05, 0.2]$, $y \in [0.8, 0.95]$) to prevent core element displacement.

A ‘Template Compliance Verification Module’ is introduced to check generated templates for grid ratio deviation, core element offset, and safe zone infringement. If devi-

ations exceed 5%, latent vectors are reverse fine-tuned to ensure full compliance with rigid rules.

B. MULTI-STYLE FEATURE EXTRACTION AND RECONSTRUCTION EXPERIMENT

Based on the optimized StyleGAN model after training, a multi-style feature extraction workflow is designed: First, the model’s mapping network transforms a random latent vector z (1×512 dimensions) into a style vector w (1×1024 dimensions). This w is fed into the synthesis network. Intermediate feature maps are extracted from each resolution block (4×4 , 8×8 , ..., 1024×1024) within the synthesis network. Each resolution block outputs a 256-channel feature map. With 18 resolution blocks, this yields a total of 4608 feature channels. Next, Principal Component Analysis (PCA) is applied to reduce the dimensionality of the extracted features. The top 128 principal components, accounting for 90% of the cumulative variance contribution, are retained to obtain a 1×128 -dimensional style feature vector. This vector represents the core stylistic features of a single poster. Finally, K-means clustering ($K=5$) is performed on the feature vectors of all samples across the five style categories. The feature vectors of each cluster center are calculated and defined as “style prototype vectors,” corresponding to minimalist style (w_1), retro style (w_2), tech style (w_3), hand-drawn style (w_4), and Chinese-inspired trend style (w_5), achieving a quantitative representation of multi-style features [27].

The ‘single-style feature control accuracy’ is measured by dual indicators: 1) Feature decoupling accuracy—proportion of generated results conforming to preset parameters when independently controlling a single style feature (e.g., adjusting color without changing layout), calculated via cosine similarity (threshold ≥ 0.85 for qualification); 2) Generated feature error rate—standardized Euclidean distance between generated features and target features (e.g., RGB deviation, layout coordinate offset).

IV. DESIGN AND GENERATION OF UNIFIED TEMPLATE STRUCTURES FOR BRAND POSTERS

Fusion Algorithm for Multi-Style Features and Template Structures

To achieve the generation objective of “switchable multi-style features with fixed template structures,” a fusion algorithm based on a “feature-template mapping matrix” was designed. The core process comprises three steps: Step 1: Constructing Template Area Feature Mappings The unified template is divided into five functional zones (logo area, core information area, auxiliary information area, decorative zone 1, decorative zone 2). For each zone, a random forest algorithm establishes the mapping relationship between “style prototype vectors” and “visual parameters,” which include color (HSV values), typography (font type/size/weight), and graphic elements (type/opacity/size). For example, in the core information zone, the mapping parameters for the tech-style prototype vector w_3 are “HSV (210,0.8,0.9), Roboto

Bold font, 120pt size, geometric lines as graphic elements.” while the national-chic prototype vector w_5 corresponds to “HSV (0,0.9,0.8), Fangzheng Kai Bold font, 110pt size, traditional patterns as graphic elements.” This mapping enables precise alignment between distinct stylistic features and template regions. Step two involves adjusting style feature weights by introducing the “style blending coefficient β ” ($\beta \in [0,1]$). This supports generating templates with either a single style ($\beta=1$ corresponds to a specific style prototype vector) or blended styles ($\beta_1+\beta_2+\dots+\beta_n=1$, $n \leq 5$). For example, $\beta_3=0.6$ and $\beta_5=0.4$ indicate a 6:4 blend of tech style and national trend style. where visual parameters across template regions are weighted by blending coefficients. For instance, the core information area’s HSV color values become: $(210 \times 0.6 + 0 \times 0.4, 0.8 \times 0.6 + 0.9 \times 0.4, 0.9 \times 0.6 + 0.8 \times 0.4) = (126, 0.84, 0.86)$, enabling flexible style blending. Step three involves post-processing of generated templates to optimize visual consistency after style fusion: - Edge smoothing algorithms (Gaussian blur, $\sigma=0.5$) are applied at transitions between regions to prevent color or element discontinuities;

- Adaptive contrast adjustment (modifying gamma val-

ues based on style type, e.g., retro $\gamma=1.2$, tech $\gamma=0.9$) ensures overall visual harmony; Finally, brand element verification checks logo and standard font positioning/sizing against brand guidelines via template matching algorithms. Deviations exceeding 5% trigger automatic corrections to ensure brand compliance in generated templates [28-30].

The dynamic adaptation tier adopts a ‘content-aware adaptive algorithm’ to handle variable content: 1) Text overflow: Adaptive font scaling (minimum not lower than VI-specified font size) combined with semantic line breaking, maintaining line spacing at 120%-150% of font size for readability; 2) Image aspect ratio changes: Core area preservation with edge gradient filling (matching the primary color tone) to avoid main subject displacement; 3) Multi-format adaptation: Preset regional ratio adjustments for 6 mainstream formats— poster (1:1/4:3/16:9), Banner (16:9), social media card (1:1/9:16)—e.g., compressing auxiliary information areas to 10% and expanding core visual areas to 70% for Banner formats. The performance table of StyleGAN2-ADA model optimization and multi style feature decoupling control strategy is shown in Table 2:

Table 2. Performance Table of StyleGAN2-ADA Model Optimization and Multi Style Feature Decoupling Control Strategy

Component/Strategy	Key Design & Technical Details	Performance Improvements & Experimental Results
StyleGAN2-ADA Basic Architecture: Mapping Network	- Composed of 8 fully connected layers; maps 128-dimensional random input vector Z to 256-dimensional style space vector W. - Integrates “style vector interpolation” for continuous style variation. - Adds Batch Normalization layer to reduce impact of sample distribution differences.	- Enhances model generalization on cross-industry brand poster samples by 28%. - Lays foundation for fine-grained control of multi-style features.
StyleGAN2-ADA Basic Architecture: Generator	- Progressive growing structure (from 4×4 to 1024×1024 pixels); each layer includes convolution, normalization, and Leaky ReLU activation.	- Improves texture edge clarity of generated posters by 35% (resolves StyleGAN1 checkerboard artifacts). - Provides technical interface for “layered control of multi-style features”.
StyleGAN2-ADA Basic Architecture: Discriminator	- Symmetric progressive structure with generator; optimizes parameters via “real poster vs. generated poster” binary classification. - Integrates ADA (Adaptive Discriminator Augmentation) technology: randomly applies cropping, rotation, color jitter to input images.	- Reduces FID (Fréchet Inception Distance) on test set from 28.6 to 16.3. - Avoids overfitting in small-sample training by forcing discriminator to focus on core features (layout, brand elements) instead of noise.
Decoupling Control Strategy: Feature-Layer Matching Mechanism	- Color system features $\rightarrow$ low-resolution layers (4×4 - 32×32): maps color vector (RGB, saturation, contrast) to AdaIN parameters of these layers. - Layout features $\rightarrow$ middle-resolution layers (64×64 - 256×256): adds “layout constraint module” to limit core element coordinates (Logo, title). - Graphic elements $\rightarrow$ high-resolution layers (512×512 - 1024×1024): combines Canny edge detection to optimize detail clarity. - Font features $\rightarrow$ full-resolution layers (32×32 - 1024×1024): uses attention mechanism to enhance text-background contrast.	- Color restoration accuracy reaches 92.3% (42% higher than traditional global control). - Layout consistency rate of cross-style posters rises from 58% to 91%. - Graphic detail restoration reaches 89.7%; font recognition accuracy improves by 38%.
Decoupling Control Strategy: Feature Interaction Constraint Module	- Color-font constraint: adjusts font spacing to 15% of font size (vs. default 10%) when color saturation $> 60\%$. - Layout-graphic constraint: triggers re-generation if graphic overlap with “graphic area” $< 80\%$. - Global consistency constraint: sets VI-compliant thresholds (main color ratio 30%-60%, Logo offset $\leq 10\%$) and auto-corrects outliers.	- Reduces conflict rate of multi-style feature control from 32% to 7%. - Significantly improves visual coordination of generated posters.
Custom Training: Model Structure Optimization	- Adds “feature mapping layer”: converts 4 style vectors to formats matching corresponding generator layers (32D for color, 64D for layout). - Introduces “brand feature embedding module”: extracts brand features (Logo contour, exclusive color) via ResNet50, compresses 1024D features to 256D (feature distillation), and embeds into 64×64 - 1024×1024 layers.	- Solves single input format limitation of traditional StyleGAN. - Improves brand recognition of generated posters by 45%. - Enhances brand feature matching degree by 52% (vs. traditional GAN loss).
Custom Training: Parameter & Process Optimization	- Training parameters: Adam optimizer ($\text{lr}=0.001$ for low-res, 0.0005 for mid-res, 0.0001 for high-res), batch size=16, 500k iterations (100k low-res, 200k mid-res, 200k high-res + constraint module). - Phased training: Stage 1 (color control), Stage 2 (layout/font + brand embedding), Stage 3 (graphic + constraint module). - Performance monitoring: evaluates FID, style restoration, brand recognition every 10k iterations; stops when $\text{FID} \leq 16.3$ (20k stable iterations) and style restoration $\geq 90\%$.	- Final model achieves FID=14.8, style restoration=91.2%, brand recognition=88.5% on test set (outperforms generic StyleGAN2-ADA). - Ensures stable training of high-resolution layers and balanced efficiency/memory usage.

V. EXPERIMENTAL VALIDATION AND EFFECTIVENESS EVALUATION OF UNIFIED TEMPLATE GENERATION

To validate the effectiveness and practicality of unified templates, a multidimensional experimental validation plan was designed. Experimental data sourced from three real brands (FMCG Brand A, Digital Brand B, Food & Beverage

Brand C), each providing 100 historical posters as test samples. Corresponding unified templates were generated using the optimized StyleGAN model and fusion algorithm, evaluated through both technical metrics and user subjective assessments.

User subjective evaluation employed a combined ap-

proach of “expert scoring + target user research”: Ten professional graphic designers (with over five years of brand design experience) were invited to rate the generated templates across four dimensions—“Brand Alignment,” “Visual Appeal,” “Information Readability,” and “Style Consistency”—each scored out of 10 points. The average scores for the three brands were 8.7, 8.9, and 8.5, respectively. Notably, Digital Brand B achieved Style Consistency. “The average scores for the three brands were 8.7, 8.9, and 8.5 respectively. Digital Brand B achieved the highest score in “Visual Appeal” (9.2), attributed to its optimal alignment between technological aesthetics and template structure. Additionally, online surveys were distributed to each brand’s target audience (Brand A: women aged 18-25; Brand B: men aged 25-35; Brand C: all age groups),

yielding 900 valid responses (300 per brand). Statistics on user responses to three questions—“Can you quickly identify the brand?” “Are you willing to pay attention to the poster information?” “Do you find the style consistent and aesthetically pleasing?”—showed affirmative responses at 94.7%, 89.3%, and 91.2%, respectively. This indicates that the generated templates resonate strongly with their target user groups. willingness to engage with poster content, “and” perception of stylistic consistency and visual appeal.” The results showed affirmative responses at 94.7%, 89.3%, and 91.2% respectively, indicating strong acceptance of the generated templates among target audiences. Table 3 shows the effect table of the unified template architecture design of brand posters and StyleGAN adaptation mechanism:

Table 3. Brand poster unified template architecture design and StyleGAN adaptation mechanism effect table

Component/Strategy	Key Design & Technical Details	Performance Improvements & Experimental Results
Design Principles of Unified Template	1. Brand Recognition Priority: Core areas (Logo position, main color ratio) follow brand VI standards with deviation $\leq 5\%$ to ensure cross-style consistency. 2. Scenario Flexibility: Non-core areas (auxiliary graphics, text layout) adjust dynamically for festivals, new products, or public welfare.	- Lays a standardized foundation for balancing “style diversity” and “structural unity”. - Lowers operational threshold, enabling non-design staff to create compliant posters.
Three-Level Template Architecture: Core Fixed Layer	- Logo Area: Fixed bounding box (e.g., top-left corner, size=15% of poster width $\times$ 10% of height); brand standard color, 100% opacity.	- Ensures stability of core brand elements; no style-related changes to avoid recognition loss. - Serves as the immutable framework for unified template structure.
Three-Level Template Architecture: Style Adaptation Layer	- Auxiliary Color Module: Auto-generates 2-3 auxiliary colors based on main color (HSV color space: hue $\pm 30^\circ$, saturation $\pm 15\%$); auxiliary color ratio $\leq 20\%$.	- Resolves “fixed-dynamic” element connection issues; ensures natural style integration. - Maintains visual harmony while supporting style diversity.
Three-Level Template Architecture: Dynamic Change Layer	- Main Visual Graphics: Scenario-specific graphics generated based on style (e.g., fireworks for festivals, product renderings for new products); confined to “graphic area” defined by the style adaptation layer.	- Carries style diversity features; adapts to different communication scenarios. - Avoids over-decoration while enhancing style expressiveness.
Template-StyleGAN Adaptation: Parameter Injection Module	- Core Fixed Layer Injection: Converts Logo coordinates/main color bar size into “bounding box constraint vectors”; injects into StyleGAN generator’s middle-resolution layers (64×64 - 256×256); “coordinate masking” limits parameter updates to ensure no core element offset.	- Embeds template rules into StyleGAN; ensures generated elements comply with template boundaries. - Eliminates core element offset (e.g., Logo) and dynamic element over-range issues.
Template-StyleGAN Adaptation: Feature Coordination Generation Mechanism	1. Initialization: System loads brand-specific template parameters and style feature vectors after user selects brand/style (e.g., “Huawei-Tech Style”, “The Palace Museum Cultural and Creative-Ancient Style”). 2. Core Generation: StyleGAN generates core fixed layer elements (Logo, main color bar, core text box); bounding box constraints ensure compliance.	- Shortens single poster generation time from 4-6 hours (traditional design) to 25-30 minutes; efficiency improved by 92%. - 91% of generated posters comply with template structure standards (vs. 58% for traditional methods).
Design Principles of Unified Template	1. Brand Recognition Priority: Core areas (Logo position, main color ratio) follow brand VI standards with deviation $\leq 5\%$ to ensure cross-style consistency. 2. Scenario Flexibility: Non-core areas (auxiliary graphics, text layout) adjust dynamically for festivals, new products, or public welfare.	- Lays a standardized foundation for balancing “style diversity” and “structural unity”. - Lowers operational threshold, enabling non-design staff to create compliant posters.

VI. CONCLUSION

This study addresses the challenges of multi-style feature coupling, inconsistent templates, and low efficiency in traditional brand poster design by proposing a StyleGAN-based technical solution. This methodological advancement is essential for the industry, providing a highly efficient way to rapidly generate and maintain consistent visual brand identity across its numerous, stylistically diverse seasonal collections and product lines. A multidimensional dataset comprising 12,000 samples was constructed, and the StyleGAN model architecture was optimized to achieve decoupled control of features such as color and layout, improving single-feature control accuracy by 42%. A three-tier unified template architecture and fusion algorithm were designed, achieving a 91% cross-style template consistency rate while reducing generation time to 25-30 minutes. Experimental validation demonstrated 91.2% style fidelity and 88.5% brand recognition in generated posters, earning approval

from professional designers and target users. This approach supports standardized brand visuals and efficient creation while expanding generative AI applications in structured design scenarios. This dual benefit is of great utility to the industry, enabling swift, consistent creation of promotional materials across diverse seasonal collections, thus professionalizing its global marketing presence and ensuring visual alignment with its core brand identity.

AUTHOR CONTRIBUTIONS

Lei Wei designed, collected and analyzed the data, and drafted the manuscript. Lei Wei conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Lei Wei participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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