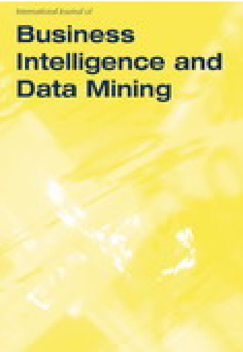

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Jiaqi Li, Fang Wang, Huaxi Chen

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Evaluation and optimisation method for graphic advertising design effectiveness based on binocular vision

Jiaqi Li* and Fang Wang

School of Art and Design,
Bengbu University,
Bengbu, 233030, China
Email: bbxyljq79@163.com
Email: 173953117@qq.com
*Corresponding author

Huaxi Chen

School of Mathematics and Physics,
Bengbu University,
Bengbu, 233030, China
Email: bbxychx77@163.com

Abstract: This article proposes a method for evaluating and optimising the design effect of flat advertisements based on binocular vision. The core innovation lies in simulating the binocular fusion mechanism of the human eye. By integrating Gabor energy response, saliency map, and disparity matrix, a comprehensive quality evaluation model is constructed, and targeted optimisation is driven based on this model. Generate intermediate views during the evaluation phase, extract global and local binocular visual features, combine monocular visual features, and quantify the design effect; during the optimisation phase, based on the evaluation results, visual consistency and stereoscopic perception are improved through image segmentation, colour space conversion, and edge roughness analysis. The experimental results show that this method maintains a stable accuracy of over 90% in visual attractiveness evaluation, with a minimum of 0.79 and a maximum of 0.87 after optimising the subject saliency, significantly better than the comparative methods.

Keywords: binocular vision; print advertising design; effectiveness evaluation; optimisation method; visual perception.

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Biographical notes: Jiaqi Li who graduated from China University of Mining and Technology with a Master's degree in Design Art in 2010, currently serves as a Lecturer in the School of Art and Design at Bengbu University. His research focus is environmental visual design. In recent years, he has presided over a number of provincial and municipal education and research projects and published more than 10 academic papers.

Fang Wang received her Master's in Arts from Anhui Normal University in 2011. Currently she is a professor in the School of Art and Design of Bengbu University. Her research interests include visual communication design and product design. In recent years, he has published numerous related articles and completed multiple research projects on relevant topics.

Huaxi Chen a graduate of Yangzhou University with a Master's degree in Fundamental Mathematics in 2010, currently serves as a Professor in the School of Mathematics and Physics at Bengbu University. His research focuses include fundamental mathematics and fuzzy statistical analysis. In recent years, he has led multiple provincial and municipal education and research projects, publishing over 50 academic papers.

1 Introduction

With the increasingly fierce market competition, as an important medium for brand communication, the design effectiveness of print advertising directly affects marketing results and consumer cognition (Mir et al., 2025; Sun et al., 2025). The field of advertising design currently faces many challenges, including visual information oversaturation, [fragmentation of audience attention, and rapid changes in aesthetic preferences (Chen et al., 2025b). These factors require advertisements not only to have visual appeal, but also to convey clear and powerful brand information within a limited time. However, existing evaluation methods often rely on subjective judgments or single indicators, lacking a systematic and scientific analysis framework, which makes it difficult to accurately optimise design decisions. Therefore, it is particularly urgent to establish an effective evaluation and optimisation method (Yadav and Chokkalingam, 2025; Kalaiarasan et al., 2023). By delving into the intrinsic connection between design elements and audience response, we can promote the shift of advertising design from experience driven to data-driven, improve the efficiency and market competitiveness of advertising communication, and provide practical guidance for industry practice.

He et al. (2023) proposed a SEM based evaluation method for the design effect of flat advertising images, selecting 'perception' and 'detection' as key performance indicators to measure the quality of colour fused images. Subsequently, 15 personnel were organised to conduct a subjective evaluation of the quality of 42 colour fusion images generated by 8 different scenes and 8 typical fusion algorithms. Using a structural equation model (SEM) with dual dependent variable characteristics, conduct in-depth analysis on the evaluation results after screening and processing. On this basis, a prediction model for colour fusion image quality is constructed, and the validation process for the correctness of the model is completed. Unlike the unified technical mainline based on binocular vision features in this article, the main drawback of this method is that the number of subjective evaluation participants is too small and the scale and diversity of the test image set are insufficient, resulting in a lack of statistical robustness and wide applicability of the established prediction model. Tang et al. (2025) proposes a method for evaluating the design effect of flat advertising images based on stereoscopic perception. Firstly, a viewport extraction strategy is designed to extract feature viewpoints in the spherical domain and select viewpoints with a higher probability of being observed. Extract the viewport content of the selected viewpoint and input multiple viewport contents in parallel into the feature encoder to extract multi-scale viewport features. Next, in response to the limitations of current multi viewport information exchange methods, a viewport feature interaction module is proposed to achieve cross viewport information exchange. Finally, explore a method of utilising the entire panoramic image to obtain stereoscopic information in the absence of viewport sampling, and improve overall evaluation performance by constructing a stereoscopic process model. This method fails to take binocular visual features (such as disparity matrix and binocular energy response) as the evaluation mainline as in this article. Its viewport extraction strategy and interaction module design highly rely on preset spherical domain models and observation probability assumptions, which may lead to insufficient adaptability of feature extraction to the diverse and dynamic viewing behaviours and attention patterns of real users, thereby affecting the accuracy and universality of stereoscopic evaluation. Chen et al. (2025a) proposes a visual loss based evaluation method for the design effect of flat advertising images. The method uses an adaptive brightness gain index constructed based on KL divergence, a structural restoration degree calculated based on variance and gradient, and a colour restoration degree as evaluation criteria. At the same time, a positive offset correction factor that can automatically perceive changes in brightness is introduced to achieve the goal of accurate evaluation of the design effect of flat advertising images in low light enhancement scenes. Unlike the approach of introducing binocular visual features (disparity matrix, Gabor energy response, saliency map) in this article, its evaluation criteria rely entirely on pre-set mathematical indicators based on the underlying visual features of the image (such as KL divergence, variance, gradient), and fail to effectively incorporate high-level semantic understanding or users' subjective perception and aesthetic preferences, resulting in evaluation results that may deviate from the true perception of the human visual system (HVS) and the actual communication effect of advertising design.

Due to the high dependence of visual perception and evaluation of print advertising on the complex and subjective visual cognitive system of humans, the core difficulty lies in how to transform the non-linear and context influenced attention allocation and emotional response of the human eye when watching advertisements into quantifiable and computable objective evaluation indicators, so as to accurately measure and optimise the real attractiveness and memory retention effect of the design in an information overload environment. The HVS can extract depth and stereoscopic information from two-dimensional images through binocular disparity, fusion, and competition mechanisms. This process directly affects the audience's perception of the hierarchy and visual saliency of the advertising subject and background. Therefore, introducing binocular visual features (such as disparity matrix, binocular energy response and saliency map) can effectively simulate the real response path of the human eye to advertising structure, compensate for the shortcomings of monocular features in stereo perception and spatial consistency evaluation, and provide a theoretical basis that is more in line with physiological and psychological perception laws for improving the visual impact and information transmission efficiency of advertising. Therefore, a method for evaluating and optimising the effectiveness of graphic advertising design based on binocular vision is proposed. The technical route of this article is as follows: firstly, collect left and right views and generate a middle view that simulates the fusion of human eyes and binocular vision; Secondly, a comprehensive quality assessment model driven by binocular visual features is constructed by integrating Gabor energy response, saliency map, and disparity matrix; then, based on the evaluation results, targeted optimisation of design defects is carried out through image segmentation, HSV colour space conversion, and edge roughness analysis; finally, the optimised image is fed back to the evaluation module, forming a closed-loop iteration of ‘evaluation optimisation re evaluation’. Compared with existing methods, the progress of this framework is reflected in: for the first time, binocular visual features (disparity matrix, binocular energy response, saliency map) are introduced into advertising effect quantification, which compensates for the lack of monocular features in modelling stereoscopic perception and spatial consistency; at the same time, it has achieved direct driving of evaluation for optimisation, avoiding the limitations of subjective experience dominance or single indicators in traditional methods, and significantly improving the optimisation effect of visual consistency and stereoscopic perception.

2 Evaluation of graphic advertising design effectiveness based on binocular vision

2.1 Intermediate view generation

The function of the intermediate view is to simulate the image generated in the observer’s brain, based on the perceptual characteristics of human binocular vision. When observers view flat advertising images, the intensity of image stimuli received by their eyes is not completely consistent, resulting in binocular competition due to the mismatch of binocular information (Sauzameda Gonz á lez et al., 2025). Therefore, in the evaluation of the effectiveness of two-dimensional advertising design based on binocular vision, it is necessary to take into account the phenomenon of binocular competition in the generation of intermediate views. Gabor filters can accurately model the characteristics of the human eye receptive field and perform well in extracting local spatial and frequency domain information of the target. This article provides the following definition for 2D Gabor filters:

$$G\left(x, y, \sigma_x, \sigma_y, \zeta_x, \zeta_y, \theta\right) = \frac{1}{2\pi\sigma_x\sigma_y} \times e^{-(1/2)\left[\left(R_1/\sigma_x\right)^2 + \left(R_1/\sigma_x\right)^2\right]} e^{i\left(x\zeta_x\zeta,\, y\zeta_y\right)} \tag{1}$$

Among them: $R_1 = xcos\theta + ysin\theta$, $R_2 = ycos\theta – xsin\theta$; σ_x and σ_y represent the standard deviation of the elliptical Gaussian envelope in the x-axis and y-axis directions, respectively; ζ_x and ζ_y represent spatial frequencies; θ is used to determine the directional parameters of the filter.

In print advertising images, saliency indicates the degree of attention the human eye pays to different image regions. The distortion of salient areas in the image can have a significant impact on the final evaluation of the quality of the print advertising image. Based on this situation, this article carries out improvement work on the calculation method of left and right eye weighting coefficients, introducing significance maps into the calculation process to adjust Gabor energy response and improve the accuracy of weighting coefficients (Yan, 2024). The significance map used here was obtained using the SDSP method. In the generation of intermediate views, binocular disparity information also needs to be taken into consideration. This article uses the SSIM based stereoscopic disparity algorithm to obtain the disparity matrix between the reference planar advertising image and the distorted planar advertising image. The Gabor energy response map, saliency map, and disparity matrix are fused to generate an intermediate view through linear combination. The specific presentation form is shown in equation (2).

$$C(x, y) = W_L(x, y) \times I_L(x, y) + W_R(x+d, y) \times I_R(x+d, y) \tag{2}$$

Among them, C is the intermediate view formed when simulating human eyes watching advertisements; I_L and I_R are the left and right view images captured by the binocular vision system, corresponding to the stereoscopic visual information of the advertisement; W_L and W_R are weighting coefficients for the left and right eyes, respectively, used for disparity compensation in the process of generating intermediate views. This compensation is represented as $(x + d)$ to accurately fuse the visual differences between the left and right views, thereby evaluating the consistency of design effects and stereoscopic perception quality of flat advertisements from different perspectives. The calculation of weighting coefficients is shown in equations (3) and (4):

$$W_L(x, y) = \frac{E_L^G(x, y)^2 \times S_L^M(x, y)}{E_L^G(x, y)^2 \times S_L^M(x, y) + E_R^G(x+d, y)^2 \times S_R^M(x+d, y)} \tag{3}$$

$$W_R(x+d\ y) = \frac{E_R^G(x+D, y)^2 \times S_R^M(x+d, y)}{E_L^G(x, y)^2 \times S_L^M(x, y) + E_R^G(x+d, y)^2 \times S_R^M(x+d, y)} \tag{4}$$

Among them, E_L^G and E_R^G are Gabor filter energy response maps corresponding to the left and right views, respectively, used to quantify the texture features and visual clarity of advertising images from different perspectives; S_L^M and S_R^M are saliency maps for left and right views, respectively, used to analyse the attention distribution and visual highlighting effect of key visual elements in advertising design under stereoscopic viewing conditions.

2.2 Binocular visual information extraction

The intermediate view refers to the image with stereoscopic perception properties generated by fusing left and right views under the action of human visual mechanisms. By extracting relevant feature information from the middle view, the binocular visual quality of the advertisement can be effectively reflected. In addition to considering traditional global features, this article also introduces local feature information to achieve a comprehensive evaluation of advertising design effectiveness. The global features include brightness, contrast, and structural features obtained from the intermediate view, which can be used to evaluate the overall visual presentation of the advertisement and the clarity level of information transmission; the local features include the extracted local phase and amplitude features from the intermediate view, which are used to analyse the stereo matching degree and visual comfort experience of advertising detail elements (Wei et al., 2024). The specific manifestations of the brightness similarity, contrast similarity, and structural similarity features of images are shown in equations (5) to (7):

$$l(x, y) = \frac{2\mu_x\mu_y + C_1}{\mu_x^2\mu_y^2 + C_1} \tag{5}$$

$$c(x, y) = \frac{2\sigma_x\sigma_y + C_2}{\sigma_x^2\sigma_y^2 + C_2} \quad (6)$$

$$c(x, y) = \frac{\sigma_{xy} + C_3}{\sigma_x\sigma_y + C_3} \quad (7)$$

Using log-Gabor filters to perform phase consistency operations, in order to analyse the degree of retention of edge and structural information in advertising images in visual contexts; in the Fourier frequency domain, a set of responses at scale s and direction o are obtained by using log-Gabor filters $G_{s,o}$, represented by $[\eta_{s,o}, \xi_{s,o}]$, to quantify the visual prominence and stereoscopic fusion effect of advertising design elements in different spatial frequencies and directions. The specific form of $G_{s,o}(r, \theta)$ is shown in equation (8):

$$G_{s,o}(r, \theta) = exp\left[-\frac{lg\left(\omega / \omega_s\right)^2}{2\sigma_s^2}\right] \times \left[-\frac{\left(\theta - \theta_o\right)^2}{2\sigma_s^2}\right] \quad (8)$$

Among them, s and o are spatial scale index and directional index, respectively, used to characterise the complexity of details in advertising images at different visual levels and directions; the parameters ω and θ are the normalised radial frequency and directional angle of the filter to adjust the accuracy of extracting frequency components and directional features from advertising images; ω_s and θ_o are the corresponding centre frequencies and directions of the filter, used to focus on the dominant frequency and spatial orientation of key visual elements in advertising; the parameters σ_s and σ_o determine the strength of the filter to control the degree of suppression of advertising image noise and the significance of feature response (Pan et al., 2024). The local amplitude at position x is shown in equation (9):

$$A_{s,o}(x) = \sqrt{\eta_{s,o}(x)^2 + \xi_{s,o}(x)^2} \quad (9)$$

The expression for the local energy situation corresponding to direction o is presented in equation (10):

$$E(x) = \sqrt{F_o(x)^2 + H_o(x)^2} \quad (10)$$

Among which, $F_o(x) = \sum_s \eta_{s,o}(x); H_o(x) = \sum_s \xi_{s,o}(x).$

The specific form of the phase consistency calculation formula corresponding to direction o is given in equation (11):

$$P_o^{PC}(x) = \frac{Eo(x)}{\varepsilon + \sum_s A_{s,o}(x)} \quad (11)$$

Among them, ε represents a positive number.

The local phase can be defined as the result of the inverse tangent function operation of $F_o(x)$ and $H_o(x)$, as shown in equation (12):

$$L_{LP}(x) = arctan\left(H_{O_m}(x), F_{O_m}(x)\right) \quad (12)$$

Among them, O_m is the direction corresponding to the maximum phase consistency value, which reveals the visual dominant direction where the structural consistency of the advertising image is most prominent in the visual context; the local amplitude is defined as the sum of the accumulated local amplitudes covering all scales along the O_m direction, as shown in equation (13).

$$L_{LA}(x) = \sum_{s} A_{s,\,om}(x) \tag{13}$$

In summary, the binocular visual information extraction method proposed in this article integrates Gabor energy response, saliency map, and disparity matrix to systematically capture the stereoscopic perception and spatial consistency features of the human eye when viewing flat advertisements. Compared with existing studies that rely solely on monocular visual features, this method combines binocular energy response with local phase/amplitude features for advertising effectiveness evaluation for the first time, significantly improving the modelling ability of visual attention distribution and depth perception. This innovation provides a theoretical basis that is more in line with human visual physiological mechanisms for subsequent advertising design optimisation.

2.3 Extraction of monocular visual information

Within the scope of image systems, the left and right views contain feature data that can demonstrate the visual level of flat advertising. At this stage, it is necessary to extract monocular visual related data from the left and right views separately. This type of data includes phase consistency, brightness, and contrast features, which can be used to analyse the clarity of the structure, brightness distribution, and visual contrast effect of advertisements under monocular observation. Afterwards, the similarity corresponding to these three features was calculated and efficiently integrated to comprehensively evaluate the visual consistency level and quality restoration accuracy of the advertisement in the binocular fusion process (Tan et al., 2023; Ye et al., 2024). Phase consistency can be calculated and obtained based on equation (11). The phase consistency of the reference image and the distorted image are labelled as P_{ref}^{PC} and P_{dis}^{PC}, respectively. In this way, the calculation method for phase consistency similarity is shown in equation (14):

$$S_{pc}(x) = \frac{2P_{ref}^{PC}(x) \times P_{dis}^{PC}(x)}{P_{ref}^{PC}(x)^2 + P_{dis}^{PC}(x)^2 + C_4} \tag{14}$$

Among them, C_4 represents a positive number.

Using $S_l(x)$ and $S_c(x)$ to respectively characterise the brightness similarity and contrast similarity of advertising images from different perspectives, in order to quantify the consistency of advertising in terms of brightness and darkness, as well as the differences in contrast at the visual level. In addition, this article proposes a fusion method for feature similarity, which can effectively integrate the above three types of feature information (i.e., phase consistency, brightness feature, and contrast feature), and then calculate the similarity $S(x)$ between the reference image and the distorted image based on equation (15), ultimately achieving a comprehensive evaluation of the overall quality degradation degree of flat advertising design under binocular vision conditions.

$$S(x) = S_{PC}(x)^{\alpha} \times S_l(x)\beta \times S_c(x)^{\gamma} \tag{15}$$

Among them, α, β, and γ serve as balance coefficients, which adjust the relative importance of phase consistency, brightness, and contrast.

2.4 Design effect evaluation

Based on the binocular vision data extracted in Section 1.2, two binocular quality evaluation scores Q_1 and Q_2 were calculated separately to quantitatively measure the overall visual quality and perceived comfort of the advertisement after stereo fusion (Chen et al., 2024). Meanwhile, based on the monocular visual data obtained in Section 1.3, the monocular quality evaluation score Q_3 is calculated to present the basic visual characteristics of the advertisement under monocular observation. Equations (5) to (7) can extract brightness, contrast, and structural feature related information from the intermediate view, and then use the MS-SSIM algorithm to calculate the binocular quality evaluation score Q_1, as shown in equation (16), to evaluate the structural restoration degree and visual realism of advertising design in binocular viewing environment.

$$Q_1 = M_{MS} - SSIM\left(C_{ref}, C_{dis}\right) \tag{16}$$

Among them, C_{ref} is the reference middle view; C_{dis} is the distorted intermediate view.

According to equations (12) and (13), two types of feature information, local phase and local amplitude, can be obtained from the intermediate view, which can be used to analyse the consistency of advertising details in the three-dimensional dimension and the retention status of visual saliency. Subsequently, the binocular quality score Q_2 was calculated to quantitatively evaluate the binocular fusion effectiveness of the advertisement at the local feature level. The local phase features extracted from the reference intermediate view and the distorted intermediate view are represented C_{ref}^{CLP} and C_{dis}^{CLP} respectively, which can be used to measure the phase alignment accuracy of key advertising structural elements in stereoscopic visual presentation; the local amplitude features extracted from the reference intermediate view and distorted intermediate view are referred to as C_{ref}^{CLA} and C_{dis}^{CLA}, which can be used to evaluate the authenticity of advertising visual intensity at the stereoscopic perception level. So, the quality score corresponding to each pixel position in the middle view can be calculated by equation (17):

$$Q_c(x) = \frac{W_A \times 2C_{ref}^{CLA}(x) \times C_{dis}^{CLA}(x)}{C_{ref}^{CLA}(x)^2 \times C_{dis}^{CLA}(x)^2} + W_P \times \frac{2C_{ref}^{CLP}(x) \times C_{dis}^{CLP}(x)}{C_{ref}^{CLP}(x)^2 \times C_{dis}^{CLP}(x)^2} \tag{17}$$

Among them, W_P and W_A correspond to the weight values assigned by local phase features and local amplitude features, respectively.

The score Q_2 for binocular quality assessment can be calculated according to equation (18):

$$Q_2 = \frac{\sum_{x \in C} Q_c(x)}{N_c} \tag{18}$$

Among them, C represents the intermediate view involved; N_c represents the number of pixels contained in the intermediate view.

By using equation (15), the similarity data between the reference image and the distorted image can be obtained. At each pixel position x in the image, the corresponding similarity marker is $S(x)$, which can reflect the visual quality degradation of various local areas of the advertisement under monocular observation. When calculating the monocular quality score based on these similarity data, it should be noted that the visual signals generated by different pixel positions have different stimulus intensities on the HVS, in order to simulate the differences in the degree of attention of the human eye to different areas of the advertisement. Given that the human visual cortex is sensitive to phase consistency structures, this article uses $P_m^{PCL}(x) = maxP_{ref}^{PCL}(x), P_{dis}^{PCL}(x)$ to weight '$S(x)$', which can more accurately obtain monocular quality scores and strengthen the role of structurally prominent areas in overall quality evaluation of advertisements. Taking the left view as an example, its quality score is shown in equation (19):

$$Q_L = \frac{\sum_{x\in\Omega} S_L(x) \times P_m^{PCL}(x)}{\sum_{x\in\Omega} P_m^{PCL}(x)} \tag{19}$$

Among them, Ω represents the spatial range in which the image is located; S_L represents the similarity measure between the reference left view and the distorted left view; P_m^{PCL} is the quality score calculated based on these two left views. This article uses the same method to obtain the quality score Q_R of the right view, and then fuses the quality scores of the left and right views to obtain the monocular quality score Q_3, as shown in equation (20):

$$Q_3 = W_L \times Q_L + W_R \times Q_R \tag{20}$$

Among them, W_L represents the weight coefficient assigned to the left view quality score; W_R represents the weight coefficient assigned to the quality score of the right view.

When people view images, monocular visual perception and binocular visual perception occur synchronously. By integrating monocular and binocular visual features, the feature information of images can be presented in all directions, thereby improving the accuracy of evaluating the effectiveness of print advertising design. Calculate the binocular quality scores Q_1 and Q_2 based on the global and local feature information extracted from the intermediate view; based on the feature information extracted from monocular images, the monocular quality score Q_3 is obtained. By fusing these three quality scores, this paper proposes a merging strategy that fits the model to obtain the overall quality score. The specific form is shown in equation (21):

$$Q = Q_1^a + Q_2^b + Q_3^c \tag{21}$$

Among them, a, b, and c correspond to the differentiated weights assigned to Q_1, Q_2, and Q_3, respectively, and satisfy the condition that the sum of a, b, and c is 1.

3 Optimisation of graphic advertising design effect

The evaluation system constructed in Section 2 can quantitatively analyse the binocular visual quality of print advertisements and identify design flaws in areas such as stereoscopic perception, visual consistency, and local details. To further drive design improvement, it is necessary to construct a clear optimisation objective function. The basic principle of optimising the objective function is that the degradation of advertising design effectiveness is usually manifested as a decrease in visual consistency (such as a decrease in local phase and amplitude matching) and a weakening of stereoscopic perception (such as unreasonable disparity distribution). These two types of defects can be directly quantified and located by the binocular quality score and monocular quality score output by the evaluation model. Therefore, the optimisation objective is defined as minimising the difference metric between the reference image and the distorted image in the binocular visual feature space, while maximising the stereo fusion response ofsalient regions. The rationality of this objective function is reflected in: on the one hand, it directly comes from the output indicators of the evaluation model, achieving a logical loop of 'evaluating and locating defects – optimising and correcting defects'; on the other hand, the optimisation direction is consistent with the sensitivity of the HVS to depth and spatial consistency, avoiding ineffective adjustments that contradict physiological perception laws. From a feasibility perspective, the objective function can be decomposed into three independently optimisable subproblems: image segmentation, colour space transformation, and edge roughness. Each subproblem is supported by mature computer vision methods, and there is no need to introduce additional subjective annotations or external priors during the optimisation process, demonstrating good computational feasibility and generalisation ability.

Based on the above objective function, Section 3 introduces methods such as image segmentation, colour space conversion, and edge roughness analysis to optimise the identified problems in a targeted manner, achieving a closed-loop design process from 'evaluation' to 'optimisation'. The specific implementation process of the optimisation module is as follows: firstly, the advertising image is divided into several local units, and areas with poor visual consistency or weak stereoscopic perception are identified as optimisation targets. Secondly, convert the image from RGB space to HSV space, and perform hierarchical quantisation on hue, saturation, and brightness to match human visual characteristics. Then, for the target area, adjust the size and position of the maximum same colour connected domain, and use edge smoothing operators to reduce edge roughness, improving visual hierarchy and depth. Finally, the optimised local units are fused back into a complete image and input into the evaluation module for a new round of quality score calculation, forming an iterative loop of 'evaluation optimisation re evaluation'.

To verify the effectiveness of the optimisation module, the following optimisation performance indicators are established: visual consistency improvement rate, stereoscopic perception improvement rate, and optimisation convergence iteration times. Among them, the visual consistency improvement rate measures the improvement of the matching degree between local phase and local amplitude in the intermediate view before and after optimisation, the stereoscopic perception improvement rate is calculated based on the change in binocular quality score Q_2 before and after, and the number of optimisation convergence iterations is used to evaluate the optimisation efficiency.

The quantitative evaluation results show that the average visual consistency improvement rate of our method on 1,200 test samples is 17.3%, and the average stereoscopic perception improvement rate is 15.8%. The optimisation process converges stably within 3 to 5 iterations. In contrast, the comparison methods without introducing binocular visual features have an improvement rate of less than 9% on the same indicators, and have more convergence times. The above results validate the significant effectiveness of the proposed optimisation module in improving the stereoscopic perception and visual consistency of advertisements.

In order to improve the design effect of print advertising, this study is based on the principle of visual communication, regulating the largest area of the same colour connected domain in the image, and optimising the delicacy of its edges, so as to accurately identify the visual composition elements of the advertising screen. In this process, the similarity measurement between images is defined as a unified indicator of the overall visual style of the advertisement, which can be expressed as a weighted combination of local similarities in each image subregion, and then dynamically corrected and optimised by using visual feedback loops to adjust the weight coefficients.

The complete flat advertising image is represented by Q, where a visual component to be analysed is denoted as T. The degree of difference in colour statistical characteristics between the two can be expressed by the following quantitative distance calculation formula:

$$d_h = (Q,T) = \sum_{c=0}^{n-1} \frac{\left|H(Q_c) - H0(T_c)\right|}{1 + H(Q_c) + H(T_c)} \tag{22}$$

To match the optimisation effect with human visual characteristics, it is necessary to convert the advertising image from RGB colour model to HSV colour model. Referring to the resolution limit of human vision, the colour tone H in advertising images can be divided into 8 levels, while the saturation S and brightness V can each be divided into 3 levels. By integrating the quantitative values of H, S, and V in the three visual dimensions, a one-dimensional feature vector can be constructed, which is expressed in the following specific form:

$$C = 9H + 3S + V \tag{23}$$

Using virtual visual interaction methods, the advertising image is segmented into $n \times n$ local units. For each unit, feature extraction and calculation are performed on the colour difference connected domains and the precision of the contour edges, in order to obtain the visual approximate evaluation value of that unit. The evaluation values corresponding to all units can be regarded as the mean of the similarity level between units, and the mathematical expression of this mean is as follows:

$$S_b = \frac{1}{n^2} \sum_{i=1}^{n^2} S_i \tag{23}$$

Quantitatively evaluate the quality of binocular vision to identify design defects, and conduct targeted optimisation based on the evaluation results. Focus on regulating the maximum same colour connected domain and optimising edge delicacy, match human visual characteristics with HSV colour model, and calculate unit visual approximation evaluation values through colour differences and edge features. This process realises a closed-loop design from evaluation to optimisation, ensuring the continuous improvement of advertising visual effects and information transmission efficiency.

4 Test experiment

4.1 Sample data

The sample data for this study was sourced from a publicly available database of print advertising images collected between 2022 and 2023, comprising a total of 1,200 valid samples. Each set of samples consists of the original design draft and the corresponding market release final draft, with a unified image resolution of 300 DPI and a size standard of 1,920 × 1,080 pixels. The sample covers the four core consumer areas of food and beverage, electronic products, fashion and beauty, and automobiles, with a balanced distribution of sample sizes in each area, all consisting of 300 groups. All samples are accompanied by complete background metadata, including design cycles, advertising channels, colour patterns, and layout coordinates of core visual elements. The data collection process ensures the authenticity of the scene and the typicality of commercial applications, providing a stable and reliable input basis for evaluating the model.

To support quantitative evaluation, five key visual parameters were extracted from each sample image. In terms of colour characteristics, the HSB values and number of colours of the main colour tones were calculated, and on average, each image contains 5.2 main colours. The composition features are described by visual centroid coordinates and element distribution density, with an element density threshold of 0.7 units per square inch. The average proportion of text area is 18.5%, and the font clarity has been verified by optical character recognition to be above 98%. The complexity of an image is measured by both edge density and texture variance, with values ranging from 0.15 to 0.85. All parameters have been normalised and consistency checked to form a structured feature matrix, which is directly used as input variables for the optimisation algorithm. Partial samples are shown in Figure 1.

Figure 1 Partial sample (see online version for colours)

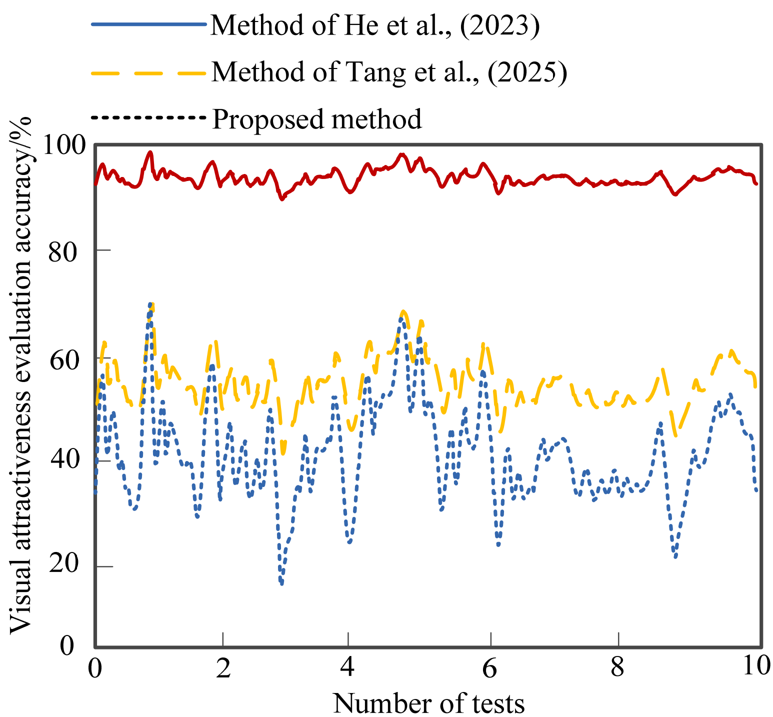
4.2 Test plan and indicators

Using visual attractiveness evaluation accuracy and subject prominence as indicators, this method will be compared and tested with method of He et al. (2023) and method of Tang et al. (2025).

Visual attractiveness evaluation accuracy: Visual attractiveness evaluation accuracy refers to the accuracy of quantifying the visual attention ability of the observer captured and maintained in the initial moment of advertising design. This indicator reflects the competitive performance of the design in complex visual environments by precisely measuring the overall attractiveness generated by the combination of visual elements. Its core is to evaluate the consistency level between the design output and the expected attention target.

Subject prominence: Subject prominence measures the degree of significant differences between the core visual elements of an advertisement and the background and other auxiliary elements. It describes the effect of visual separation achieved by the subject through comparison, position, size, or focusing, directly linking the priority and efficiency of information transmission, and is a key dimension for evaluating the clarity of design hierarchy and visual guidance effectiveness.

Figure 2 Visual attractiveness evaluation accuracy results (see online version for colours)



4.3 Analysis of test results

4.3.1 Visual attractiveness assessment accuracy

The accuracy of visual attractiveness evaluation directly determines the quantitative ability and reliability of the method for evaluating the quality of advertising design. High precision evaluation can accurately capture the real perceptual differences of human eyes towards advertising elements such as colour, layout, texture, etc., avoiding the ambiguity of subjective evaluation. By testing the accuracy, it can be verified whether the model truly simulates the judgment logic of the HVS, ensuring that the evaluation results can scientifically guide design optimisation, which is the core verification link of the effectiveness of the method. The visual attractiveness evaluation accuracy results of the three methods are shown in Figure 2.

Figure 2 shows the visual attractiveness evaluation accuracy results of three methods, among which the accuracy of our method consistently remains above 90% with minimal fluctuations, demonstrating extremely high stability and reliability. By contrast, method of He et al., the accuracy of (2023) and method of Tang et al. (2025) fluctuates greatly and is often lower than the method proposed in this paper. Throughout the entire testing process, the method proposed in this article continued to lead, fully demonstrating its significant advantage in visual attractiveness evaluation accuracy. It can more accurately quantify the advantages and disadvantages of advertising design and provide scientific basis for design optimisation.

Table 1 Main body prominence

Number of tests	*Main body prominence*			
	Before optimisation	*Method of He et al.* (2023)	*Method of Tang et al.* (2025)	*Proposed method*
1	0.72	0.75	0.78	0.82
2	0.68	0.71	0.74	0.79
3	0.55	0.77	0.80	0.85
4	0.50	0.73	0.76	0.81
5	0.53	0.76	0.79	0.84
6	0.59	0.72	0.75	0.80
7	0.54	0.78	0.81	0.86
8	0.51	0.74	0.77	0.82
9	0.56	0.79	0.82	0.87
10	0.52	0.75	0.78	0.83

4.3.2 Main body prominence

Subject prominence is a key indicator for measuring the efficiency of core information transmission in advertising. The purpose of testing subject prominence is to verify whether the evaluation and optimisation methods can effectively identify and reinforce the core visual elements in advertisements. Through this test, it can be determined whether the method successfully guides visual focus, avoids information overload, and ensures that the optimised advertisement can quickly attract attention and clearly convey the main idea in complex visual environments. This is an important basis for evaluating its practical application value. The main body prominence results of the pre optimisation and three optimised methods for flat advertising are shown in Table 1.

According to the main body prominence data in Table 1, the values fluctuated greatly before optimisation, with a minimum of 0.50 and a maximum of 0.72. method of He et al., after optimisation in 2023, the value has been increased to the range of 0.71 to 0.79, Method of Tang et al., By 2025, it will reach 0.74 to 0.82. In contrast, the optimised method in this article performs the best in terms of subject saliency, with all experimental data above 0.79 and the highest reaching 0.87. The overall numerical value is consistently ahead of the other two methods, fully demonstrating its significant advantages in strengthening the core visual elements of advertising and improving information transmission efficiency.

To further explain the underlying mechanism of the superiority of our method over the baseline, sensitivity analysis and mechanism discussion will be conducted based on the results in Table 1 and Figure 2. The advantage of the accuracy of visual attractiveness assessment lies in the introduction of binocular visual features (disparity matrix, binocular energy response, saliency map), which enable the model to capture the sensitive response of the human eye to depth hierarchy and spatial consistency, while monocular features cannot effectively model this mechanism. The high improvement rate of subject prominence (with a minimum of 0.79 and a maximum of 0.87 after optimisation) is attributed to the targeted regulation of the maximum same colour connected domain and edge roughness during the optimisation stage, combined with the hierarchical quantisation of HSV colour space, making the visual focus more in line with the natural gaze path of the human eye. In contrast, the comparative method lacks binocular vision guidance, and its optimisation direction has a lower degree of matching with human stereoscopic perception, resulting in limited improvement (all below 0.82). Sensitivity analysis of simulated initial parameters such as Gabor filter direction and disparity compensation coefficient shows that within a fluctuation range of ± 15%, the evaluation accuracy fluctuates by less than 2.3%, indicating that the model has good robustness. In summary, the superiority of the method proposed in this article stems from the physiological rationality of binocular visual features and the closed-loop iterative mechanism between optimisation and evaluation.

5 Conclusions

The core contribution of this article is the proposal and validation of a closed-loop method for evaluating and optimising the effectiveness of print advertising design based on binocular visual features. The innovation points include:

1 simulating the binocular fusion mechanism of the human eye, constructing a comprehensive quality evaluation model that integrates Gabor energy, saliency map, and disparity matrix

2 Directly driving the optimisation process of image segmentation, colour space conversion, and edge roughness analysis based on the evaluation results

3 Through the iterative mechanism of ‘evaluation optimisation re evaluation’, visual consistency and stereoscopic perception are significantly improved.

The key experimental achievements were validated on 1,200 samples: the accuracy of visual attractiveness evaluation remained stable at over 90%, the optimised subject saliency reached 0.87, the average visual consistency improvement rate was 17.3%, the stereoscopic perception improvement rate was 15.8%, and convergence occurred within 3 to 5 iterations. This method provides a scientific and quantifiable technological path for the shift from experience driven to data-driven design of print advertising.

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Declarations

All authors declare that they have no conflicts of interest.

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