Research on the Innovation of Visual Communication Art in Brand Communication Strategy in the Digital Era

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Abstract: In this paper, we first extract visual elements from the pattern, color, and copy features of brand products using saliency detection methods. Based on the multi-instance collaborative learning mechanism, combined with the semantic correlation relationship between samples, user connection, social distance and other social factors, the correlation between data and brand entities is reasoned to accurately obtain brand entity information. Finally, the social brand entity information is used to optimize the brand value communication strategy of the information flow, including the innovation of intelligent advertisement and scenario-based visual communication, as well as the interactive intelligent advertisement of the social information flow. The practical application found that the brand relevance accuracy detection rate is up to more than 0.93, and the NDCG of visual communication element evaluation of different brands is between 0.93.9 and 0.98.6. The best relevance coefficient and communication effect is achieved when the three elements of pattern, color and copy are combined, with the relevance coefficient reaching 0.95 and the conversion rate being 2.9%. In the digital era, the innovation of visual communication art provides more inspirations and strategic support for brand communication, helping brands to better establish association with consumers in the digital era, and realizing the enhancement of brand image and maximization of communication effect.
Keywords: Saliency Detection; Semantic Association; Brand Value; Communication Strategy; Digital Era

1. INTRODUCTION

With the rapid development of the digital era, brand communication strategies are facing unprecedented changes and challenges. The rapid development of information technology and the widespread popularization of social media have resulted in fundamental changes in the way brands interact with consumers, which not only changes the way consumers obtain information, but also affects the brand shaping and communication path (Anand, 2020; Verčič, 2021). Visual communication art, as an important part of brand communication, conveys brand concepts and product information to the target audience through visual elements such as graphics, colors, and text (Kujur & Singh, 2020; Lim & Kim, 2021). In the digital era, visual communication design not only enhances the brand memory point, stimulates its purchase desire, and promotes effective communication between brands and consumers (Acan & Aygenc, 2022). How to effectively utilize visual communication art in the digital era to enhance the effect of brand communication has become an important topic of current research. In recent years, a number of scholars have conducted research on brand communication strategies in this digital era, pointing out that social media platforms have become the main channels for brand communication, and brands need to utilize these platforms to publish appealing visual content. For example, social media platforms have become a major channel for brand communication, and brands need to utilize these platforms to publish appealing visual content. For example, Mangiò, F notes that social media platforms have become a major channel for brand communication, exploring the persuasive power of brands on social media through an analysis of consumer engagement on Facebook. Studies have shown that the way brands communicate on social media has a significant impact on their persuasive effect (Mangiò et al., 2024). Stachowiak-Krzyżan, M. analyzed the interaction of young Polish consumers with fast-fashion brands on social networking platforms, focusing on the social media on Facebook, Instagram, Pinterest and YouTube platforms to motivate participation in fashion brand communication activities. It is argued that brands can expand their reach and credibility by encouraging users to share their experiences and product photos (Stachowiak-Krzyżan, 2021). Al-Fikri, I et al, emphasized the impact of social media communication on consumers' perspectives of Samsung brands, which demonstrated that brand activity and content quality on social media can significantly influence consumers' brand perceptions and attitudes (Al-Fikri & Roostika, 2023). Social media platforms have become the et al. main channel for brand communication and it is crucial for brands to utilize these platforms to publish engaging visual content. Augmented reality and virtual reality technologies provide brands with new platforms for deeper interactions with consumers. Huang,

T. L designed dynamic 360° augmented reality panoramic environments to elucidate the formation mechanisms of personalized experiences (Huang & Liu, 2021). Green tourism destination brands were investigated to pave the way for the actual development of digital experiences. McAnally, M. pointed out the application of AR and VR technologies in apparel retailing, in order to enhance the customer experience through innovative retailing strategies, and VR vision not only attracts the attention of consumers to stimulate their desire to purchase, but also helps to enhance brand image and apparel retail sales performance (McAnally, 2020). Motion graphics and short videos are more effective than static images in attracting attention and conveying information. For example, Yang, S et al. redefined the elements of brand communication from the perspective of brand communication characteristics, combined with the principle of feature acquisition of mobile terminals. By comparing with NEWRANK index, the feasibility of brand influence evaluation model of short video publishing media is illustrated (Yang et al., 2020). Finally, it is proposed that short videos help publishing media enterprises explore new ways to quantify brand media influence.

Dong, Z. and Ma, J. point out that short videos show higher effectiveness in attracting attention and conveying information compared with static images (Dong & Ma, 2023). This means that urban brands can vividly demonstrate the unique selling points of their products or profoundly communicate the core values of the brand, thus more effectively establishing an emotional connection with the audience, thus more effectively connecting with consumers and promoting the dissemination and awareness of the brand's message.This study aims to deeply explore the innovation of visual communication art in brand communication strategy in the digital era. From the perspective of multimodal brand relevance coefficients, we use the saliency detection method to extract the most eye-catching visual elements from the pattern, color, and copy features of products. Through the collaborative learning mechanism of multiple instances and multiple models, we combine the semantic association between samples, geographic location, user connection, social distance and other social factors in the digital era to reason about the relevance of social media data and brand entities. The brand information in social media will be concluded to explore the innovative strategies of smart ads and scenario-based visual communication, as well as the application of interactive smart ads of social information flow in brand communication. It is expected that this study can enhance brands to better associate with consumers in the digital era and promote the further development of visual communication art in the field of brand communication.

2. MULTIMODAL BRAND RELEVANCE COEFFICIENTS

2.1 Brand Visual Target Salience

The visual objective saliency of a branded product is the key to attracting consumer attention. Through the visual attention objective model, bottom-up saliency detection method, the most compelling visual elements can be extracted from the pattern, color, and copy features of the product (Guo et al., 2021). It provides an important visual basis for subsequent brand relevance reasoning. First of all, extract the saliency feature data of brand product design target information in the extraction process, the saliency feature signal of brand product design target information is converted accordingly, and the conversion function formula is as follows:

$$f(a) = A \cdot f(x) \quad (1)$$

Where: a is the signal after conversion, A is the conversion coefficient, x is the signal before conversion. In the process of extracting the saliency characteristics of the target information of brand product design, the brightness characteristics of the product target information are obtained L:

$$L = \frac{r+g+b}{3} \quad (2)$$

Where: r, g, b denotes the corresponding values of the red, green and blue channels of the brand product design target information, respectively. In the color feature extraction of brand product design target information, its brightness feature is first normalized to generate various colors from the color channel. Take the red and blue color features as an example, its color feature extraction formula is:

$$\begin{cases} R = r - \frac{g+b}{2} \\ B = \frac{g+b}{2} - \frac{|g-b|}{2} - r \end{cases} \quad (3)$$

Where: R is red feature, B is blue feature. Based on this, to achieve the saliency feature extraction of brand product design target information, there are brightness features, color features.

2.2 Brand Relevance Detection and Integration Mechanism

Accurate relevance measurement is the foundation for developing an effective brand communication strategy. By understanding what content is highly relevant to the brand, brand managers can design visual communication art in a more targeted way to optimize the communication of the brand message (Diaz-Garcia et al., 2023). Using a multi-task multi-model, the brand relevance detection process is shown in Figure 1, the whole process is divided into two steps, relevance detection and relevance integration. For the target brand text content relevance detector, visual feature relevance detector, on the basis of extracting features for each media content individually, train both differentators to determine the degree of semantic relevance of the content of its corresponding modality to the target brand entity.

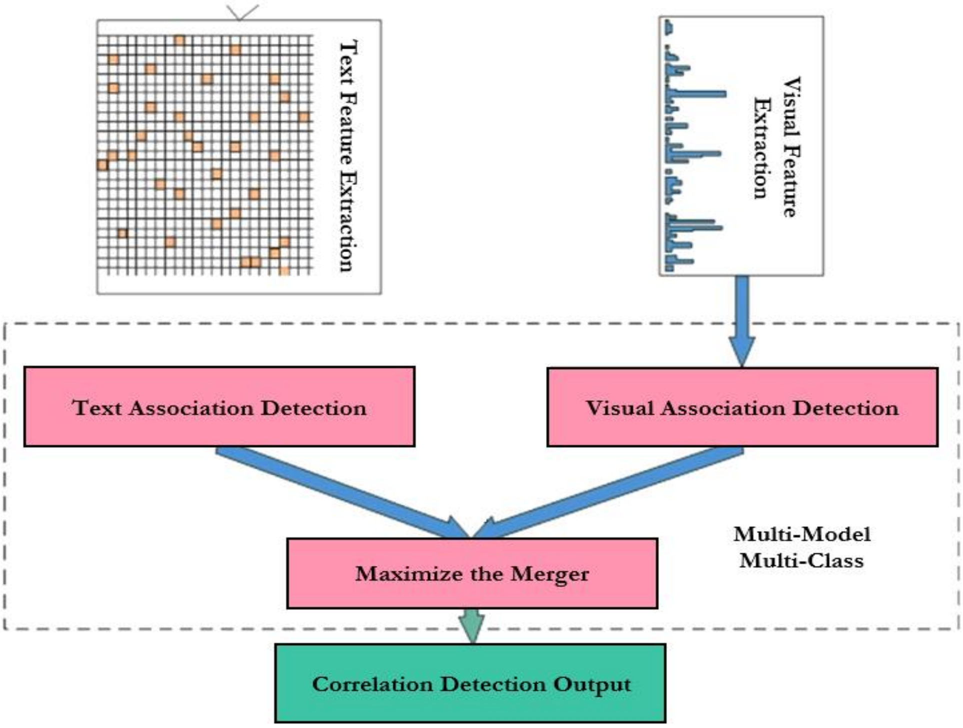


Figure 1: Brand relevance detection process

The decision values are transformed into coefficients of content relevance by Sigmoid function:

$$r_{t/v}(m,b) = \frac{1}{1+exp(-\omega X_{t/v}(m,b))} \qquad (4)$$

Where: $X_{t/v}(m,b)$ Decision value of the textual or visual SVM model output, the output of the textual/visual content relevance detector of the samples is mapped to a uniform (0,1) interval through a Sigmoid function transformation. In order to maximize the possibility of detecting the samples associated with the target brand entity, a recall maximization strategy is used to integrate the sample-target entity relevance coefficients. Correlation coefficients of samples with target entities:

$$r(m, b) = max\{r_t(m, b), r_v(m, b)\} \quad (5)$$

Where: $r(m, b)$ is the correlation coefficient between a sample m and the target entity b, $r_t(m, b)$ is the text content correlation coefficient, and $r_v(m, b)$ is the visual content correlation coefficient (Meesala & Subramanian, 2022). By maximizing the merging strategy, the samples of the test samples that are associated with the textual content, or visual content of the target entity will be selected for the next stage. It is also relevance online inference to achieve the optimization of relevance coefficients.

2.3 Similarity Relationship Graph Construction

In order to improve the accuracy of content classification of brand association, the labeled sample collection and the classified sample collection provide auxiliary information for brand entity information recognition. Figure 2 shows the brand association sample similarity relationship, the labeled data refers to some of the manually labeled data, and the classified data refers to for the data that has been classified in the data with high classification confidence. In this paper, the graph model is utilized to represent the similarity relationship between the labeled samples, the classified samples and the test samples, i.e., to establish the similarity relationship about these data. The similarity between the labeled digital content, the classified samples and the test samples is calculated, and then, through the similarity between the sample features, a sample similarity relationship graph is established, which is represented in the form of an adjacency matrix.

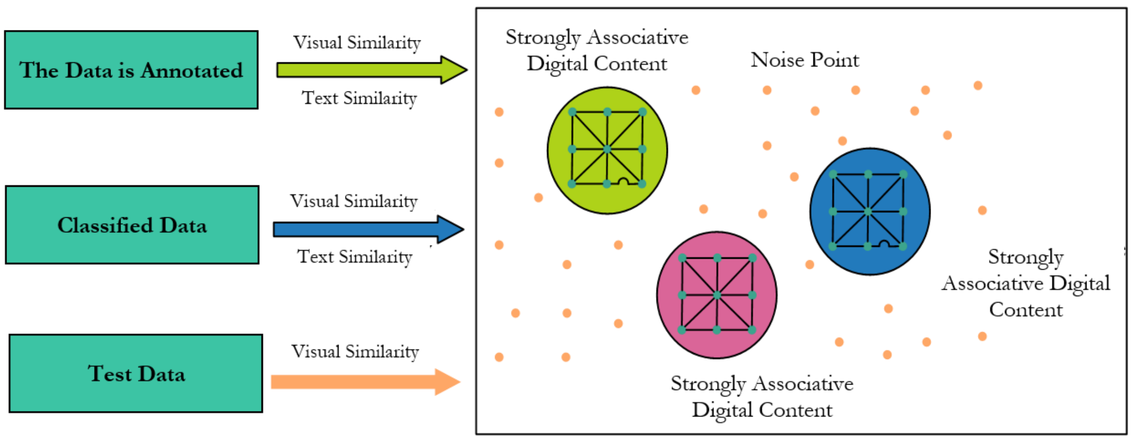


Figure 2: Similarity relationship of brand association samples

For the similarity between samples, it is mainly obtained by calculating the distance between two modal contents, textual content and visual content, between different samples:

$$\rho(m_i, m_j) = \alpha\rho_t(m_i, m_j) + (1-\alpha)\rho_v(m_i, m_j) \qquad (6)$$

Where: $\rho_t(m_i, m_j)$ and $\rho_v(m_i, m_j)$ are textual content similarity and visual content similarity respectively (Hiriyannaiah et al., 2022). a is the weight parameter between the two similarities, and here a is set to the empirical value of 0.65. The textual content similarity and visual content similarity are calculated as follows:

$$\rho_{t/v}(m_i, m_j) = exp\left(-D(t_{t/v})\right) \qquad (7)$$

Where: $D(t_{t/v})$ denotes the distance between the textual visual features of two samples (Tembhurne & Diwan, 2021). Due to the large size of nodes in the generated similarity relation graph and the presence of large noise connections, it is necessary to preprocess the similarity relation graph to find the set of digital contents with strong association relationships and remove the noise connections. Therefore, a fast dense subgraph detection algorithm based on contraction expansion is used to detect dense subgraphs about test samples. For each test sample, the SEA algorithm takes it as a starting point in the similarity graph. And iteratively executes the expansion step and contraction step alternately until the algorithm converges to obtain a dense subgraph about the test samples, where all the other vertices in the subgraph are samples with strong correlation with the test samples.

2.4 Reasoning about Brand Entity Associations

In the offline detection stage of relevance, the sample relevance detector outputs the relevance coefficients of the samples with specific brands. Meanwhile, after building a sample similarity relationship graph and dense subgraph detection, a collection of samples with strong association with test sample m_t is obtained M_f. In collection M_f, each element is a labeled sample or a sample that has been classified with high classification confidence, and brand association coefficients are updated and optimized using social network information between M_f and m_t. A probabilistic graph model is constructed on the basis of dense subgraphs. A Markov random field is used to define the undirected graph $G = (V, E)$, V as the nodes in the graph and E as the edges, where each node corresponds to a random variable, and the edges between nodes indicate that there is a probabilistic dependence between the nodes' corresponding random variables. It is assumed that each node v satisfies

Markovianity, i.e., the probability that a vertex V of the graph is in a state depends only on the nearest proximal node of vertex v, and that vertex v is conditionally independent with respect to any other node in the graph. The goal of a Markov random field is to optimize the joint probability density distribution within a random field:

$$p(y_1, y_2, \dots, y_n) = \frac{1}{z}\prod_i p\,(y_i)\prod_{i,j} p\,(y_i, y_n) \qquad (8)$$

Where: $p(x_i)$ describes the probability of the current node and $p(x_i, x_j)$ describes the joint distribution between neighboring nodes. Each sample in the detected dense subgraph acts as a node and whether there is a connection between two nodes depends on the social similarity between the samples. Where social similarity mainly depends on three factors, social connection, temporal information and geographic location information (Liu et al., 2021). The social similarity of two digital contents is defined as follows:

$$s_{whole} = w_l s_l + w_s s_s + w_t s_t \quad (9)$$

Where: s_l, s_s, s_t represents geographic location similarity, social connection similarity, and temporal similarity, respectively, and w_l, w_s, w_t corresponds to the weights of the three similarities. The social connection similarity is calculated according to the following formula:

$$s_s(m_i, m_j) = \begin{cases} 1, u_i = u_j \\ 0.5, u_i \Leftrightarrow u_j \\ 0, \text{otherwise} \end{cases} \quad (10)$$

Where: $u_i \Leftrightarrow u_j$ indicates that u_i and u_j are associated in social media platforms. When the time of posting of the two samples is very different, the likelihood that there is an association between these two samples will become smaller, so the following formula is used in measuring the temporal similarity of the two samples:

$$s_t(m_i, m_j) = 1 - \frac{(|t_i - t_j|)}{\tau} \qquad (11)$$

Where: t_i and t_j are the timestamps of the postings of samples m_i and m_j, and τ is the normalization factor. After the social similarity between the samples is computed, the existence of a connection between two nodes depends on whether the similarity Swhole is greater than a threshold. The hidden variable $y = 1{,}0$ in the Markov random field is defined to indicate whether the sample is semantically related to a specific brand entity, and the observation probability is defined as:

$$p(f_i \mid y_i = 1) = r(m_i, b) \qquad (12)$$

Where: f is the textual as well as visual features of the sample, $r(m_i, b)$ is the entity relevance coefficient of the sample, and $p(f_i \mid y_i = 0) = 1 - p(f_i \mid y_i = 1)$ is obtained. Illustrates the branded entity semantic relevance probability of a single sample, which is determined by the visual, textual information and offline relevance detection process (Khan et al., 2022). The joint probability distribution in a Markov random field is defined as:

$$p(y_i, y_j) = exp(\|y_i - y_j\| s_{i,j}) \qquad (13)$$

Two connected nodes should have similar states. Definitions $y = (y_1, \dots, y_N)$ and $f = (f_1, \dots, f_N)$, the optimization objective of a Markov random field is:

$$p(y \mid f) = \prod_i p\,(f_i \mid y_i) \prod_{i,j} p\,(y_i, y_j) \qquad (14)$$

Optimization is performed using relaxed confidence transfer, through which the confidence value $p(y \mid f)$ is returned as the updated brand entity relevance coefficient.

3. BRAND VALUE COMMUNICATION STRATEGY FOR INFORMATION FLOW IN THE DIGITAL SOCIAL ERA

3.1 Innovation in Intelligent Advertising and Scenario-based Visual Communication

By integrating the above technical achievements of brand entity information retrieval into intelligent advertising innovation, a more vivid, precise and interactive advertising experience can be created, and Figure 3 shows the scenario-based visual communication intelligent advertising. Intelligent advertising combined with scenario-based visual communication dynamically adjusts the visual performance and emotional color of the advertising content through big data analysis of user behavior in different scenarios and user demand correlation data, making it highly compatible with the user's current context. Designers can make use of the characteristics of social media platforms and user behavior data to create advertisements that are more in line with users' interests and needs. For example, when users browse clothing content, the intelligent advertising system can push brand ads with hot clothing. At the same time, AR visual technology is utilized to let users appreciate the clothing products in an immersive environment, and innovative visual communication methods are used to create advertising content that meets the atmosphere of the scene and stimulates the emotional resonance of users (Oti & Crilly, 2021).

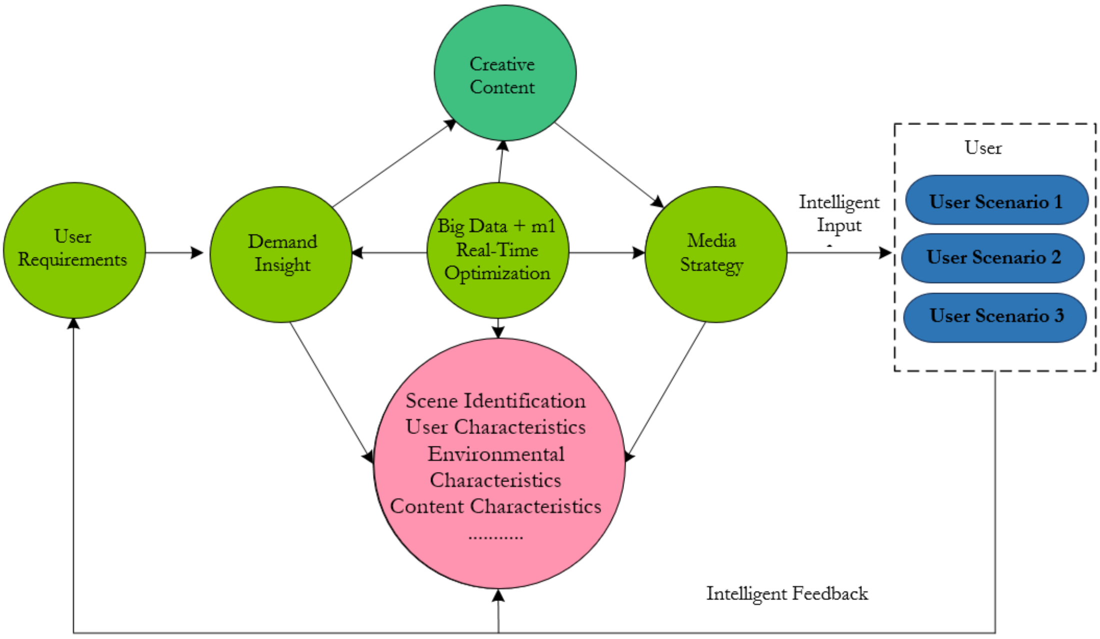


Figure 3: Scenario-based visual communication of smart ads

3.2 Interactive Smart Ads for Social Streams

Intelligent advertising maximizes accuracy, but over-personalized messages may also narrow the user's perception of the message as a result, creating an information cocoon effect that affects the brand's interactive behavior. Deep processing of information occurs when the recipient of the information is highly engaged with the subject matter or has the ability and motivation to think deeply about the details of the subject information, which creates an attitude that is more enduring and predictive of future behavior (Choi & Lim, 2020).

Therefore, attracting consumers to participate in brand interaction helps to establish deep communication between brands and consumers and form a long-lasting brand relationship. With the development of social media, social network applications represented by WeChat, Weibo, etc. have penetrated into people's living space, and technological empowerment has greatly improved user initiative and interaction, and social media marketing has become an important way of enterprise marketing (Sreejesh et al., 2020). The brand communication strategy of social information interactive intelligent advertising is shown in Figure 4, and the information flow advertising of WeChat's circle of friends is a typical representative of this model. The ads are pushed to friends with the same interests, and WeChat friends can see the likes and comments among themselves, interact with their list of friends by leaving messages, and complete the mutual brand recommendation and participate in the secondary processing and dissemination of brand information. The intelligent social distribution mode formed by combining algorithms and socialization has broken through the barriers of social distribution and algorithmic distribution, and is gradually rewriting the rules of interpersonal and group communication, becoming a new mode of advertisement dissemination, and prompting consumers to actively participate in the interaction of brand information. In this stage, smart ads are highly integrated into the real life of users by relying on their social relationships, attracting users to participate in brand interaction to the greatest extent possible (Febriani, 2021). It forms the information interaction between brands and consumers based on specific living areas, specific living objects or specific living behaviors, and realizes brand value co-creation.

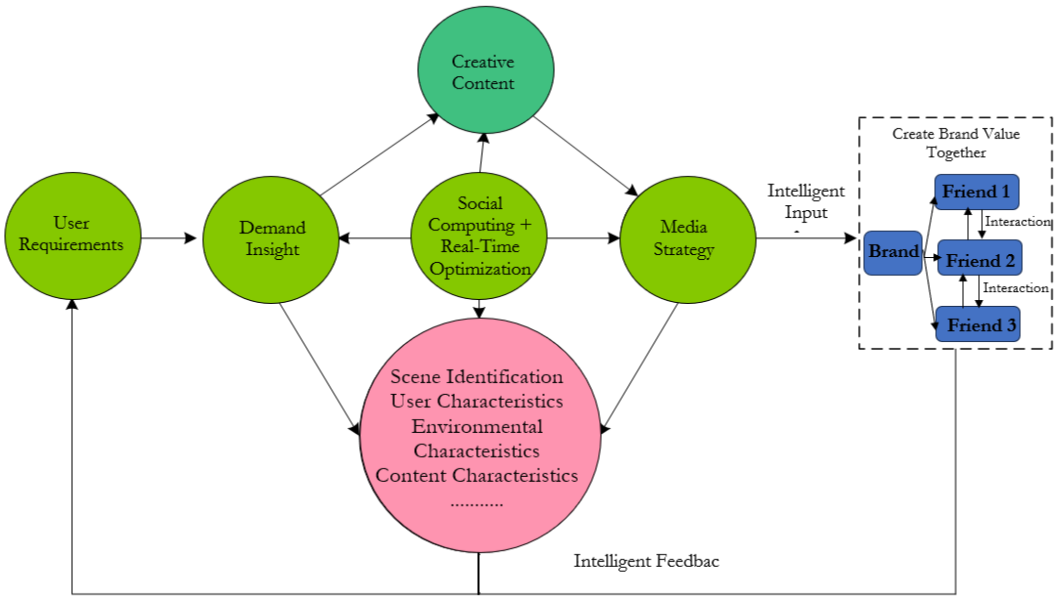
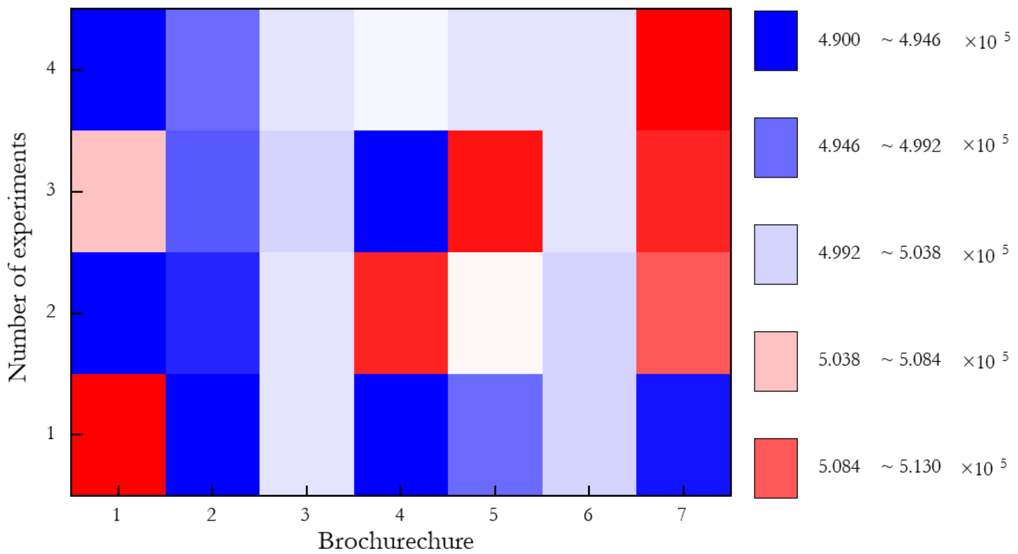


Figure 4: Brand communication strategy for interactive smart ads with social information

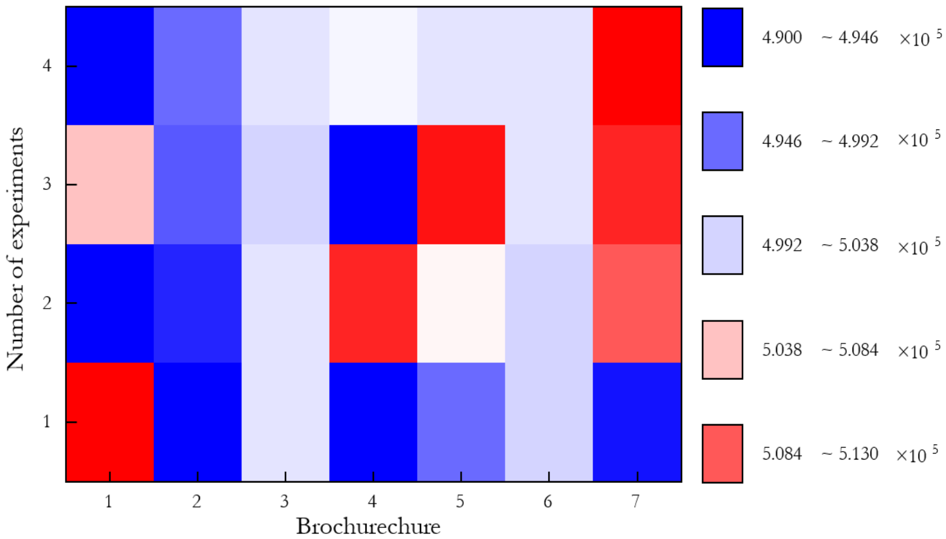
4. BRAND COMMUNICATION RELEVANCE APPLICATION

4.1 Brand Relevance Accuracy Detection

A dataset containing social media samples, brand relevance coefficients, and social network information for social connections, temporal information, and geolocation information is collected to build a text-based baseline model only for assessing the relevance of the samples to a specific brand. The brand relevance coefficients are updated and optimized using the Markov random field model proposed in this paper in combination with social network information. The two methods were compared and analyzed, and four repetitions of the experiment were conducted to ensure the accuracy of the experiment. Heatmaps of the output results were plotted in order to visually compare the effectiveness of the two methods. Figure 5 shows the comparison of brand relevance detection accuracy, compared to the baseline model, the output of this paper's method has a smaller error and higher prediction accuracy. The baseline model, as shown in Figure 5(a), has more blue color gamut as well as hue squares close to blue. It indicates that with these combinations of brand data samples and output parameters, the number of experiments is relatively high, and the range of output parameters from sample 1 to sample 6 is 4.90 × 10^5-6.19 × 10^5, and there are some fluctuations in the output parameters of the traditional baseline model between samples. , the model in this paper is shown in Fig. 5(b), the red color gamut with shades close to red increases significantly. This indicates that under these combinations of samples and output parameters, the number of experiments is relatively small under the corresponding combinations of samples and output parameters, and the range of output parameters from sample 1 to sample 6 is 4.90 × 10^5-5.13 × 10^5, showing smaller fluctuations and higher predictive stability. Aiming to reduce the error and improve the prediction accuracy, the red region mostly reflects that the model can achieve stable output results with higher brand association accuracy with less number of experiments. By integrating social network information, the method in this paper does improve the accuracy of brand association detection. For brand managers, it is crucial to understand what content is highly relevant to the brand. This is because it can help brands design their visual communication art in a more targeted way, thus optimizing the effectiveness of brand messages.



(a) Baseline model



(b) Model of this paper

Figure 5: Comparison of brand association detection accuracy

4.2 Comparison of Visual Communication Element Evaluation

Through the brand relevance detection method proposed in this paper, we can gain insight into which visual communication elements are more touching to consumers, optimize the design scheme, and enhance the brand image and its communication effect. In order to comprehensively verify the effectiveness of this paper's method, six representative datasets covering different industries, brands and product types are selected: A is the electronics brand dataset, B is the food brand dataset, C is the beverage brand dataset, D is the automobile brand dataset, E is the cosmetics brand dataset, and F is the travel brand data. A variety of testing methods were selected to compare with this paper's method, and Figure 6 shows the assessment of the relevance of brand visual communication elements. It can be seen that this paper's method performs best overall on average on the six brand data, A electronics brand dataset with an NDCG of 0.965, B food brand dataset with an NDCG of 0.978, C beverage brand dataset with an NDCG of 0.986, D automobile brand dataset with an NDCG of 0.979, E cosmetic brand dataset with an NDCG of 0.937, and F travel brand Data NDCG is 0.975. logistic regression model and multimodal fusion method of brand relevance detection is better, especially the logistic regression model, in the cosmetics brand dataset brand relevance analysis NDCG is 0.942, also slightly higher than this paper's method of a number of, this is due to the logistic regression to deal with the problem of dichotomous classification and through the weighting coefficients directly reflect the degree of influence of each feature on the results. The NDCG of the multimodal fusion method is 0.928, which is due to the fact that multimodal fusion is able to comprehensively extract the correlation between brands and consumers by taking into account a wide range of information, such as text, images, and sound. The decision tree classifier is just average, with an NDCG of 0.862, which may be due to the complex relationship between data features appearing overfitting, resulting in a decrease in generalization performance. The method in this paper achieves better performance than other methods on most datasets, especially when dealing with the beverage product dataset. The effectiveness of the brand relevance detection method proposed in this paper is verified, which provides strong data support and scientific guidance for enterprises to optimize their brand communication strategies.

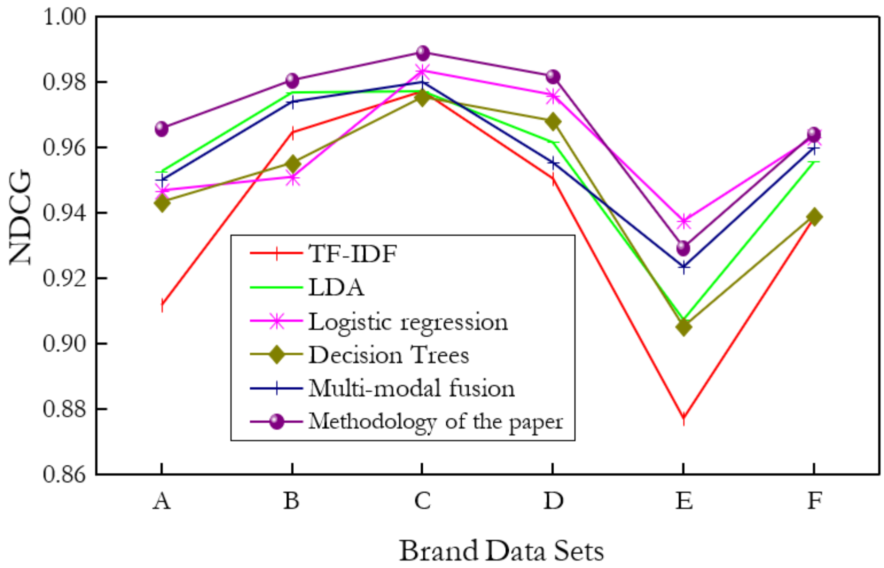


Figure 6: Evaluation of the relevance of brand visual communication elements

5. VALIDATION OF THE EFFECTIVENESS OF BRAND MESSAGE DISSEMINATION

In verifying the effectiveness of different visual communication methods in the process of brand information dissemination by analyzing the relevance of content and brands on social media, in order to quantify the contribution of each element to brand communication and provide data support for optimizing brand communication strategies. Using the relevance detector in this paper, the relevance coefficient of each piece of content to the brand is calculated, and the collected data are classified according to the visual communication elements, patterns, colors, and texts.

Table 1 shows the impact of visual communication elements on brand information dissemination, and it can be seen that visual communication elements such as pattern, color and copywriting all have a significant impact on brand information dissemination. Observing the average correlation coefficient, when pattern, color and copy are combined, the correlation coefficient and communication effect reaches the best, reaching 0.95, compared with the lowest correlation coefficient of copy among the single elements, which is only 0.67, indicating that its correlation with the brand is relatively weak. From the viewpoint of communication range, pattern + color + copywriting also performed well, communication breadth forwarding volume covered 20060 people, the widest communication range of visual communication elements. The spread depth comment count spreads reached 6087 people, but compared to the other elements, it effectively reaches a wider audience. Interaction degree of the number of likes, pattern, color and copy when the combination of the three interactive volume topped the list of 13050, positively interacted with it, which is essential to enhance brand awareness and user stickiness.

Finally, in terms of conversion rate, the combination of pattern, color and copy ranked first with a conversion rate of 2.5%, which means that the brand message conveyed through Element A can be more effectively converted into actual brand attention or purchase behavior. The single elements of color and copy have a lower conversion rate of 1.8%, indicating that they are relatively weak at getting users to take action. When these elements are used in combination, their contribution to brand message dissemination is higher, especially when pattern, color and copy are combined, the correlation coefficient and dissemination effect reaches the best. At the same time, the proportion and way of using each element can be flexibly adjusted according to different social media platforms and audience characteristics in order to achieve the best communication effect.

Table 1: Influence of visual communication elements on brand messaging

Visual Communication Elements	**Relevance Factor**	**Retweets**	**Comments**	**Likes)**	**Conversion Rate**
Patterns	0.75	12000	3500	8000	1.9%
Color	0.68	9500	2800	6500	1.8%
Copywriting	0.67	11000	3200	7500	1.8%
Pattern + Color	0.83	15000	4500	10000	2.3%
Pattern+Copy	0.85	16000	4800	11000	2.3%
Color+Copy	0.78	13000	3800	8500	2.2%
Pattern+Color+Copy	0.95	20060	6087	13050	2.9%

6. CONCLUSION

To help brands better associate with consumers in the digital era, visual saliency algorithms are used to extract saliency features of target information of brand products. Combined with the semantic association relationship between samples, user connection, social distance and other social factors, a more precise inference is made on the association between data and brand entities. In view of the characteristics of brand information in social media, the brand value communication strategy of information flow is investigated, especially the innovation of intelligent advertisement and scenario-based visual communication, as well as the interactive intelligent advertisement of social information flow. It is verified that the accuracy of brand relevance is detected as high as 0.93 or more, and the NDCG of the evaluation of visual communication elements of different brands is as high as 0.986. When these elements are used in combination, their contribution to the communication of brand information is higher, and when the pattern, color and text are combined, the relevance coefficient of 0.95 and the communication breadth of 20,060, the depth of communication of 6,087, and the degree of interaction of 13,050 Reach the best. The methodology of this paper not only provides strong support for brands to better establish association with consumers in the digital era, but also lays a solid foundation for realizing the enhancement of brand image and maximizing the communication effect, and is expected to promote the further development of visual communication art in the field of brand communication.

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