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Information Display Interaction System Design Based on Visual Communication

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In the digital era, information display interaction systems are pivotal for advertising design, yet traditional solutions suffer from information overload, inadequate interactivity, and mismatches between design and technology. To address these issues, this study develops a visual communication-based information display interaction system for advertising. The system integrates four core modules: visual presentation with hierarchical information processing, user data analysis via the Transformers model, personalized recommendations using collaborative filtering, and technical support with multi-layered security safeguards. Experimental results validate its superior performance: the advertising click-through conversion rate reaches 4%, doubling that of traditional advertising; in personalized recommendations, it achieves a precision of 0.82, recall rate of 0.78, and F1 score of 0.80, outperforming other mainstream strategies; the average response time is 250.97 ms, with a request failure rate below 5% even under high load. This system maintains robust stability and efficiency in high-concurrency scenarios, significantly enhancing advertising effectiveness. It not only proves reliable in practical application but also offers valuable insights for the optimization of future advertising information display systems.

Keywords: Information Display Interactive System; Advertising Design; Visual Communication; Personalized Recommendations; System Stability

1. INTRODUCTION

With the rapid progress of information technology [1–3], especially the popularization of the Internet, mobile devices and smart terminals, information display and interaction systems have been widely used in various industries. Whether in industrial automation, smart home, medical care, finance and other fields, the design and interaction quality of information display systems have an important impact on the efficiency of information transmission, timeliness of decisions, and user work efficiency. However, traditional information display and interaction systems generally have several design problems such as information overload, overly complex interfaces, and insufficient interactivity. These problems can easily make users feel confused or overwhelmed when faced with a large amount of information, resulting in poor operating experience, which in turn affects work efficiency and decision-making results. Therefore, how to optimize information display and interaction design and improve user experience has become a core issue that needs to be urgently addressed in the current information system design field [4–6].

In recent years, many scholars and designers have begun to focus on the optimization of information display systems and the improvement of interactive design. Minatoya et al. studied an information display system with facial expressions, which converts the information to be displayed into parts and facial expressions to construct a facial chart. This morphological data shows superiority in transmission speed, recognizability, accuracy and multi-data transmission [7]. Kang et al. introduced a desktop display system called "Reading Sharing" that aims to improve social interaction by enhancing the public reading experience of nursing home residents. The results showed that the system effectively catalyzed and encouraged people's social interaction [8]. Kamarulredzuan Moch et al. anticipated that their proposed user interface display could help manage food waste. They designed the user interface using a user-centered design method and focused on the interface design process with usability goals. The results showed that the designed user interface performed well [9]. Although these studies have provided important

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ideas for the optimization of information display interactive systems, existing research has focused mostly on one aspect, often ignoring the problems of information overload and insufficient interactivity, and there is still a large gap between technical implementation and design effect. Therefore, how to organically combine visual communication, interactive design and technical implementation has become a difficult problem requiring an urgent solution.

In order to address the shortcomings in existing research, many scholars and designers have tried to improve the design of information display systems through multidisciplinary integration. In order to explore the interface design and implementation of the airport general flight information display system, Yang Qianyun proposed an interface design scheme based on user experience, conducting system requirements analysis and utilizing a functional design, implementing the scheme through front-end technology [10]. Kristiadiet al. used Ethernet audio, information display system and IoT technology to build an Internet-based communication channel for disaster relief and patient monitoring during flood disasters in hospital environments [11]. Sakaneet al. proposed a compact optical system that forms a long-distance floating image by means of a Fresnel lens in a reflective aerial imaging optical system. Through this method, a prototype long-distance floating aerial display system using a large Fresnel lens was developed [12]. However, although these methods have been successful in specific areas, they have not completely solved the adaptation problem in cross-platform and multi-terminal environments, and often fail to fully balance the combination of interactivity and technical implementation.

In this study, we design an information display interaction system based on visual communication specifically for advertising information presentation. The system uses technologies related to visual communication [13–15] to present and display information visually, in order to improve the readability of advertising information. The Transformers [16–18] model is applied to model and analyze user data. The training goal is to maximize user interest. Based on the Transformers model, collaborative filtering algorithms [19–21] are used to implement user-based advertising information recommendations, and users are enabled to customize the system interface. According to experimental analysis, the advertising effect of this system is significantly better than that of traditional advertising. Compared with other recommendation strategies, the personalized recommendation implemented by this system shows obvious advantages. Overall, the system can provide excellent performance in terms of response speed and stability, meet user needs, and show good performance and stability. Under high load conditions, the system can still run stably and has certain flexibility and fault tolerance. In practical applications, the system can significantly improve the effectiveness of advertising and provide an effective solution for the advertising industry in terms of processing large-scale data and high-concurrency scenarios.

2. INFORMATION DISPLAY INTERACTION SYSTEM DESIGN

The system design in this paper comprises four modules: visual display and information presentation module, data processing and analysis module, intelligent interaction and personalized customization module, and technical support and security module.

2.1 Visual Presentation and Information Display Module

The visual presentation and information display module is the core module of the entire information display system, responsible for presenting advertising information to users through visual communication. The design goal is to help users quickly obtain the required information through a clear, concise and attractive interface layout, and to improve the readability, visibility and comprehensibility of information through appropriate visual presentation.

In order to help users quickly understand advertising information, it is first necessary to organize the information hierarchically through visual elements. The hierarchical structure design can guide users to quickly find the most important advertising information and ensure the overall readability and simplicity of the system. In the design of this module, a hierarchical classification formula is used to help the layering of information display:

$$Layer = \alpha \times Importance + \beta \times Proximity + \gamma \times Frequency \tag{1}$$

Importance refers to the criticality of information. It can be highlighted by using larger fonts, different colors, and special graphics. Proximity corresponds to the order and position of information. Important information should be placed at the top or center of the page to reduce the visual burden on users. Frequency indicates how often users view information. Information that users view frequently can be highlighted with unique visual logos.

When designing, the font style is extremely important. In order to determine the hierarchy of different texts, the following formula is used to calculate the visual weight of the text:

$$V_f = k_1 \times S_f + k_2 \times W_f + k_3 \times C_f \tag{2}$$

where V_f represents the visual weight of the font, S_f represents the font size, and important information uses a larger font. W_f represents the font thickness, and important information is highlighted in bold. C_f represents the font color, and the conspicuity of information is enhanced through color contrast. k_1, k_2, k_3 represent the influence of font size, thickness, and color on visual weight.

The system adjusts the color matching of the display interface by the color difference between the background color and the foreground color. The calculation formula is:

$$CR = \frac{(L_1 + 0.05)}{(L_2 + 0.05)} \tag{3}$$

where L_1 represents the relative brightness of brighter colors, and L_2 represents the relative brightness of darker colors.

The formula for calculating relative brightness is:

$$L = 0.2126 \times R + 0.7152 \times G + 0.0722 \times B \tag{4}$$

Table 1 User behavior data.

Data category	Data item	Data description
User basic information	User ID	Unique ID for the user
	Location	The user's geographical location
	Device information	The type of device with which the user is accessing the system
Advertising interaction data	Advertising impressions	The number of advertising impressions viewed by users
	Advertising clicks	The number of times users clicked on the advertising
	Advertising dwell time	The time a user stays on the advertising page after clicking on the advertising
Advertising preference data	User interest tags	The user's preferred advertising categories or topics
	Browsing history	The categories of advertisings that users have viewed, the content of the advertisings, and the specific attributes of the advertisings
	Purchase behavior	User purchasing behavior guided by advertising

where R, G, B represent the standardized valuesof the three components of red, green, and blue.

In order to help users understand complex information more easily, graphical displays are used to design complex information. Graphical displays (charts, graphs, etc.) can structure data or information through intuitive visual elements, allowing users to grasp the key points of information more quickly.

For the presentation of chart data, the following formula is used to help determine the design of the chart:

$$\text{Effective Visualization} = \sum_{i=1}^{n} (\text{Data Representation}_i \times \text{Perceptual Clarity}_i) \quad (5)$$

Data Representation$_i$ is the representation of each data element (such as bars, lines, dots, etc.), Perceptual Clarity$_i$ represents the visual clarity of each data element, taking into account the influence of factors such as color, shape, size, etc., and n represents the total number of data elements.

In the system, dynamic information display can help users gradually grasp the information through animation and progressive display. In this process, the dynamic effect not only enhances the visual appeal, but also effectively reduces the cognitive burden of users.

The duration of the animation should be adjusted appropriately according to the complexity of the information to prevent excessive animation from increasing the user's waiting time. The animation duration T is set by the following formula:

$$T = \propto \times \text{Complexity} + \rho \times \text{InformationVolume} \quad (6)$$

where $\propto$ represents the complexity of the information, ρ is the amount of displayed content, and T represents the duration of the animation in seconds. By adjusting the complexity coefficient and the information coefficient, the animation duration is reasonably set according to the specific situation to ensure that the display of advertising information is neither too long to cause redundancy nor too short to appear hasty.

2.2 Information Processing and Analysis Module

In the system designed in this paper, the information processing and analysis module plays a vital role because it directly determines the accuracy and effect of advertising display. The main task of this module is to analyze user behavior, advertising content and display effect in real time to optimize advertising display and enhance the interaction experience of the user.

2.2.1 Data Collection and Preprocessing

The purpose of data collection and preprocessing is to collect user behavior data for subsequent processing. The collected user behavior data is shown in Table 1.

The collected user data needs to be preprocessed by data cleaning, normalization, and denoising.

For multi-dimensional user behavior data, the weighted average method [22–23] is used for data integration; its calculation formula is:

$$D(t) = \sum_{i=1}^{n} w_i \cdot D_i(t) \quad (7)$$

where $D(t)$ represents the integrated data, $D_i(t)$ represents the output of the i-th data, and w_i represents the weight of each data. The weight is adjusted according to factors such as data reliability and real-time performance.

The collected data is processed for missing values. If a value is missing, the mean is used instead:

$$D(t)_{clean} = Impute(D(t)) \quad (8)$$

where $Impute(D(t))$ represents the process of supplementing missing values, and the mean is used to fill missing values.

The data are normalized to ensure that their dimensions are consistent, using the minimum-maximum normalization [24–25] method:

$$D_i'(t) = \frac{D_i(t) - \min(D_i)}{\max(D_i) - \min(D_i)} \quad (9)$$

where $\min(D_i)$ represents the minimum value of the i-th data, $\max(D_i)$ represents the maximum value of the i-th data, and $D_i'(t)$ represents the normalized data.

2.2.2 Data Analysis and Processing

The core goal of data analysis and processing is to model the user's behavior sequence and capture the dependencies between user behaviors. This paper uses the Transformers model to process the collected data of different users to achieve modeling and processing of different users' behavior data.

The core of the Transformers model is the self-attention mechanism that captures long-distance correlations by calculating the dependencies between different positions. The calculation formula for the self-attention mechanism is as follows:

$$Q = XW_Q, K = XW_K, V = XW_V \tag{10}$$

where X represents the processed user data, and W_Q, W_K, W_V represent the query weights matrix, key weight matrix, and value weight matrix obtained through training.

The calculation formula for self-attention is:

$$Attention(Q, K, V) = soft\max\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{11}$$

where d_k represents the dimension of query and key, $\frac{QK^T}{\sqrt{d_k}}$ represents the similarity between query and key, and the softmax function converts it into probability distribution, and finally outputs the weighted value V.

Since the Transformers model itself does not contain information about time or position, encoding is used to provide information about each position in the sequence. The position encoding formula is as follows:

$$PE_{(pos,2i)} = \sin\left(\frac{pos}{1000^{2i/d}}\right) \tag{12}$$

$$PE_{(pos,2i+1)} = \cos\left(\frac{pos}{1000^{2i/d}}\right) \tag{13}$$

where pos represents the position index, i represents the dimension index, and d represents the dimension of the word vector. By adding position encoding to the input data, the model can capture temporal information.

The encoder of Transformers consists of multiple self-attention layers and feedforward neural networks. The output of each layer is normalized after residual connection. The calculation formula for the feedforward neural network is:

$$FFN(x) = \max(0, xW_1 + b_1)W_2 + b_2 \tag{14}$$

where W_1, W_2 represent the weights matrix in the feedforward neural network, b_1, b_2 represent the bias terms, and the activation function performs nonlinear transformation through maximum selection.

The encoder output of the Transformers model is:

$$E = LayerNorm(x + FFN(x)) \tag{15}$$

The multi-head self-attention mechanism [26–28] is introduced to improve the expressiveness of the model. The formula for multi-head attention is:

$$MultiHead(Q, K, V) = Concat(head_1, head_2, \ldots, head_h)W^O \tag{16}$$

Each head$_i$ is calculated by a self-attention mechanism:

$$head_i = Attention(QW_i^Q, KW_i^K, VW_i^V) \tag{17}$$

where W_i^Q, W_i^K, W_i^V represent the weights matrix of the i-th head, and W^O represents the output projection matrix. Through the attention mechanism of multiple heads, the model can capture different information in multiple subspaces.

The Transformers model is trained utilizing user behavior data and advertising content data. The training goal is to optimize the model parameters by maximizing the user's interest in the advertisement so that the model can generate efficient advertisement recommendations.

The cross-entropy loss function [29–30] is used to train the advertisement click prediction task; its calculation formula is:

$$Loss = -\sum_{i=1}^{N} y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i) \tag{18}$$

where y_i represents the true label (click or not click), and $\hat{y}_i$ represents the click probability predicted by the model. In the ad recommendation stage, based on the trained model, the system can generate personalized ad recommendations for each user.

2.3 Intelligent Interaction and User Customization Module

In the proposed system, the core goal of the intelligent interaction and user customization module is to optimize the user experience. Through intelligent interaction and personalized customization, the system can provide customized advertising content and interaction methods according to the unique needs and preferences of each user.

The key to intelligent interaction design is to ensure smooth, simple and efficient user operations. This design process includes the analysis of user historical operations, preferences, and habits to identify their behavior patterns and predict potential needs. In addition, the system should provide instant feedback every time the user interacts, which can be presented in a variety of ways such as visually, through sound or vibration, to ensure a quick response and enhance the user experience. At the same time, the system should automatically adjust the interface and interactive elements according to the user's needs and behaviors in order to closely align them with the user's operating habits.

Personalization is one of the key ways to improve user satisfaction. The system can adjust the interface and information display method according to the user's interests, needs and usage habits to achieve optimization that better meets user needs. Specific designs include:

(1) Interface personalization: Users can adjust the interface layout according to their own needs, such as adjusting the theme, font, color, information display format, etc. The system makes adaptive changes based on the user's personal preferences.

(2) Dynamic advertising recommendation: The system automatically generates advertisements related to the user's interests based on the user's behavior patterns and historical records. This process is based on the collaborative filtering algorithm, which predicts other advertising information that the user may be interested in by analyzing the user's behavior data and rating data.

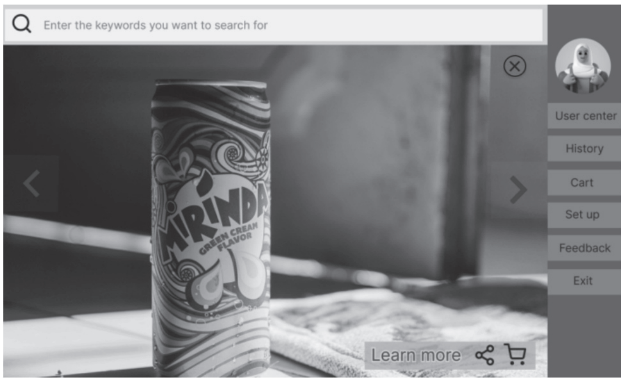

Figure 1 System interface design.

Table 2 Related technologies for implementing the system.

Technical field	Technology name	Description
Front-end technology	React.js	JavaScript library for building user interfaces
UI framework	Ant Design	For rapid development and design of interfaces
CSS Technology	SASS	Functions for enhancing CSS
Responsive design	Bootstrap	Ensures the system is adaptable to devices of various screen sizes
Back-end technology	Node.js	Node.js as the back-end JavaScript runtime
API protocol	RESTful API	Used for communication between different modules within the system
Data storage	MongoDB	Data storage solution, MongoDB supports non-relational data storage
Caching technology	Redis	Used to cache commonly used data and reduce database query pressure

The collaborative filtering algorithm is a recommendation algorithm that makes recommendations based on the user's historical behavior or the behavior of other users. This paper implements user-based collaborative filtering.

User-based collaborative filtering recommends advertising information by analyzing the similarities between different users. If two users have similar preferences in their past behaviors, the system can recommend advertising information to one of them that the other user may like.

In order to implement user-based collaborative filtering, it is necessary to calculate the similarity between users. The cosine similarity [31–32] calculation method is used to measure the similarity between users:

$$Sim(u, v) = \frac{\sum_{i=1}^{n} r_{ui} \cdot r_{vi}}{\sqrt{\sum_{i=1}^{n} r_{ui}^2 \cdot \sum_{i=1}^{n} r_{vi}^2}} \tag{19}$$

where r_{ui}, r_{vi} represent the click data of user u and user v on ad i.

For the calculation of similarity, the user-based prediction formula is:

$$\hat{r}_{u,v} = \bar{r}_u + \frac{\sum_{v \in N_u} sim(u, v) \cdot (r_{u,v} - \hat{r}_u)}{\sum_{v \in N_u} |sim(u, v)|} \tag{20}$$

Through collaborative filtering-based analysis of user behavior data, we can identify the types of ads that align more closely with user interests. The system can then dynamically adjust ad content according to these preferences to better meet user needs.

The interactive interface of the system information display is shown in Figure 1.

In the system interface, users can search, view and browse advertising information. The advertising information display feature is designed as a carousel. Users can click the arrow to view the previous or next advertisement. For advertisements of interest to them, users can click Learn More to enter the details interface. They can also forward or add products of interest to the shopping cart through the function button in the lower right corner. Users can directly click the close function button in the upper right corner of the advertisement if they are not interested in it. After closing the current advertisement, the system can display the advertisements that may be of interest to them. The function buttons on the right store user information. Users can view their personal information and modify it. The history button can be clicked to view the history of the user's browsing. The shopping cart button can be clicked to choose the items to be added to the shopping cart. The settings button can be clicked to customize the system-related layout and design.

2.4 Technical Support and Security Assurance Module

Technical support mainly includes the front-end, back-end, database and other technologies used to implement the system. Security assurance protects users' personal information, behavior data and other information. This module introduces related technologies.

The technical support used to implement the system is shown in Table 2.

As shown in Table 2, React.js is used in the front-end, and the Ant Design framework is used in the user interface (UI) design to quickly build a modern user interface. SASS is used to improve the functionality of CSS and enhance the flexibility-of-style management. In addition, the system implements responsive design through Bootstrap to ensure consistent display on different devices. The backend uses Node.js as the operating environment, and the modules exchange data efficiently through the RESTful API protocol. For data storage, MongoDB is used to support high scalability and flexible data processing. At the same time, Redis is used to cache data, thereby improving system performance and reducing the burden on the database.

When users interact and make personalized recommendations, the system needs to store user preference information (such as ad click records, favorites, ad search history, etc.). To prevent sensitive data from being illegally accessed, the Advanced Encryption Standard [33] (AES) is used to encrypt the stored data:

$$C = E_k(P) \tag{21}$$

where P represents plaintext data, E_k represents the encryption operation using the symmetric key k, and C represents the ciphertext data stored in the database.

The decryption process is expressed as:

$$\mathrm{M} = D_k(C) \tag{22}$$

where D_k represents the decryption operation, and the key k is used to decrypt the ciphertext C to restore the original data.

In order to ensure the secure transmission of data between the client and the server, the system uses Rivest-Shamir-Adleman technology [34] (RSA) during the user login process:

$$C = P^e \mod (n) \tag{23}$$

where P represents the user's plaintext data, e is the public key, n is the modulus of RSA, and C represents the encrypted ciphertext data.

The decryption process is expressed as:

$$M = C^d \mod (n) \tag{24}$$

where d is the private key, which is only held by the server, and M represents the decrypted data.

The system in this paper uses the SHA-256 hash algorithm [35–36] to encrypt sensitive data such as user passwords and account information. The hash algorithm maps data into a hash value of fixed length, and the original data cannot be reversed, which ensures that user passwords and other data cannot be directly deciphered even if they are stolen. The hash process is expressed as:

$$H = SHA - 256(P) \tag{25}$$

where P represents the user's plaintext data, and H is the generated hash value. At the same time, the system stores the password as a hash value instead of plaintext, further improving the security of the system.

3. RESULTS DISPLAY

3.1 Advertising Effect Evaluation

It is very important to analyze the advertising effect of the information display interactive system based on visual communication because it is related to the accurate delivery of advertisements, user experience and commercial returns. By monitoring the click-through rate, conversion rate and user feedback of ads, the recommendation algorithm can be optimized, the relevance and personalization of ads can be improved, and user engagement can be increased; moreover, the number of irrelevant ads can be reduced, as can ad fatigue. An experiment was conducted to analyze the advertising effects of the system designed in this paper and compare them with the traditional method of advertising. The same initial number of impressions (5,000) was controlled to analyze the conversion of the two delivery methods in the display-click-add to cart-purchase process. The funnel diagram in Figure 2 depicts the results.

According to data in Figure 2, the advertising effect of this system is significantly better than the traditional advertising effect. The probability of advertisements from display to click is 30%, which is higher than the 20% of traditional advertisements. The conversion rate from adding to the shopping cart to purchase is 17%, while the traditional advertisement is 13%; the overall conversion rate is 4%, which is twice that of traditional advertisements (2%). These data show that the proposed system not only attracts more clicks, — it can also improve the conversion from clicks to purchases, demonstrating the advantages of the system in improving advertising relevance, increasing user participation and encouraging users to make purchases.

3.2 Personalized Recommendation Effect

In order to comprehensively evaluate the performance of the advertising recommendation system, the effect of personalized recommendation was analyzed. The analysis was conducted to compare the recommendation effects of five types of recommendation algorithms: collaborative filtering, content-based recommendation, the system designed in this paper, hybrid recommendation and deep learning recommendation. The main analysis was conducted to determine the accuracy, recall rate and F1 score of personalized recommendation. The results are shown in Table 3.

As shown in Table 3, the system designed in this paper performs significantly better than other recommendation strategies in terms of precision (0.82), recall (0.78) and F1 score (0.80), indicating that the system has significant advantages in accuracy and comprehensiveness of recommendations. Compared with the system proposed in this paper, the collaborative filtering algorithm is more prominent in precision (0.72), but has a lower recall rate (0.68) and a general overall effect (F1 score = 0.70). The content recommendation strategy (precision of 0.70, recall of 0.65, and F1 score of 0.67) performed the worst and failed to meet user needs effectively. The hybrid recommendation algorithm (precision of 0.74, recall of 0.71, and F1 score of 0.72) improved in balancing precision and recall, but was still inferior to the proposed system. The deep learning recommendation algorithm (precision of 0.76, recall of 0.72, and F1 score of 0.74) performed well, but was slightly inferior to the system in this paper in all three indicators. In summary, the system designed in this paper is the best in

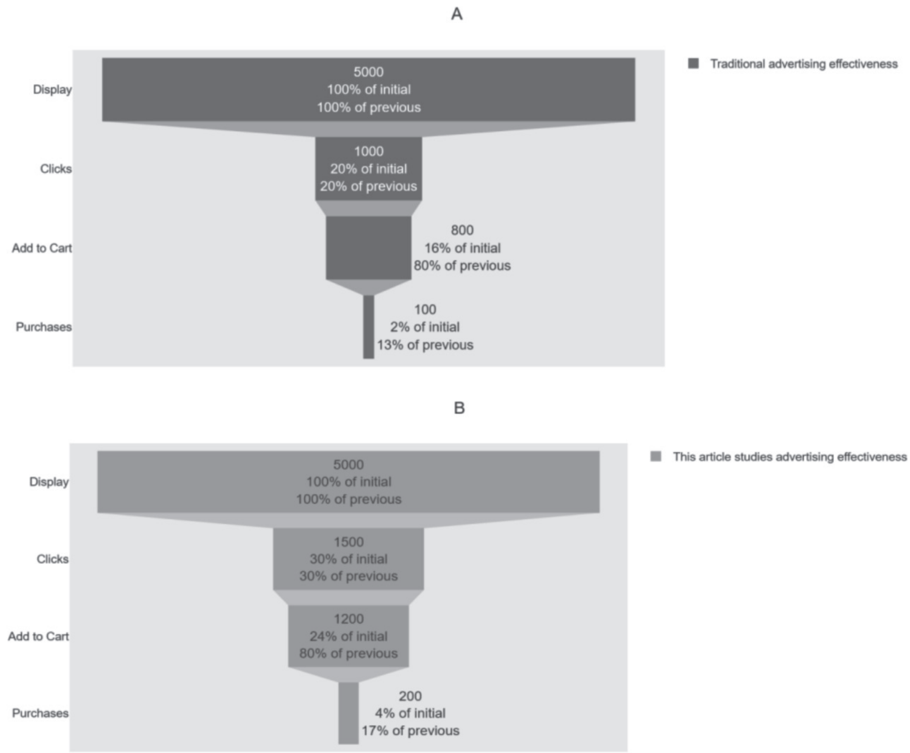

Figure 2 Figure 2 (A) Traditional advertising effect. Figure 2 (B) Advertising effect of this system. Figure 2. Advertising effect.

Table 3 Personalized recommendation results.

Recommended strategies	Precision	Recall	F1-Score
Based on collaborative filtering algorithm	0.72	0.68	0.70
Content-based recommendation algorithm	0.70	0.65	0.67
The method designed in this paper	0.82	0.78	0.80
Based on hybrid recommendation algorithm	0.74	0.71	0.72
Recommendation algorithm based on deep learning	0.76	0.72	0.74

terms of personalized recommendation effect, showing strong recommendation accuracy and effectiveness.

3.3 System Performance Analysis

It is very important to perform performance analysis on the information display interaction system based on visual communication designed in this study, because it can ensure the stability of the system under high load, thereby optimizing the user experience and the effect of the advertising display. The results of performance analysis can help to improve the efficiency of system resource utilization, speed up response, reduce error rates, and promptly discover potential bottlenecks to prevent resource waste and system crashes. In addition, performance analysis also provides a basis for system expansion and architecture optimization, ensuring that advertising content can be updated and accurately displayed in real time, further improving the stability, scalability and market competitiveness of the system. For the purpose of analysis, the designed experiment collected thousands of response times when the system was running smoothly. The analysis results are shown in Figure 3.

According to the data analysis, the average response time of the system is 250.97 milliseconds, and the median response time is 251.27 milliseconds. The two are close, indicating that the response time of most requests is stable and fast. The standard deviation of the thousand response times calculated by the data is 48.94 milliseconds, indicating that the system response time fluctuates little and has good consistency. Overall, the system can provide fast and stable responses, meet user needs, and show good performance and stability.

In order to focus on the performance of the system under high load and ensure the long-term stable operation of the system, a statistical analysis of six types of request failure reasons was conducted on 10,000 requests under normal load and high load conditions. The results are shown in Figure 4.

Based on the statistical analysis of 10,000 failed requests under normal and high loads, the results show that although the number of failed requests under high load has increased, the request failure ratio is still less than 5%. The specific data for the six types of request failure reasons are 119, 83, 76, 59, 48, and 42. Compared with 32, 24, 18, 15, 11, and 7 under normal load, the overall failure rate remains within an acceptable range. This shows that although the system experiences more request pressure under high load, it can still

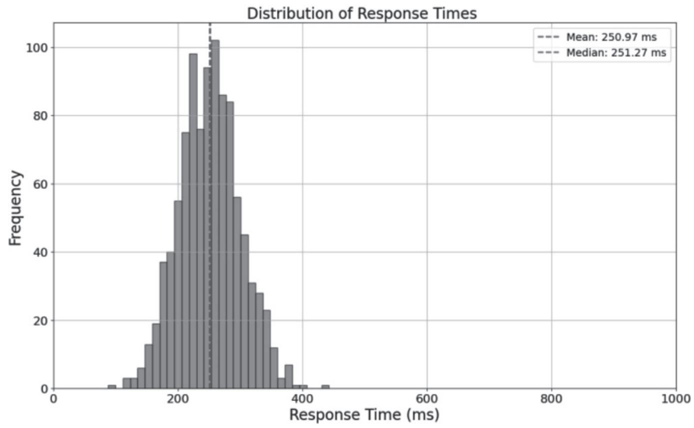

Figure 3 Response time.

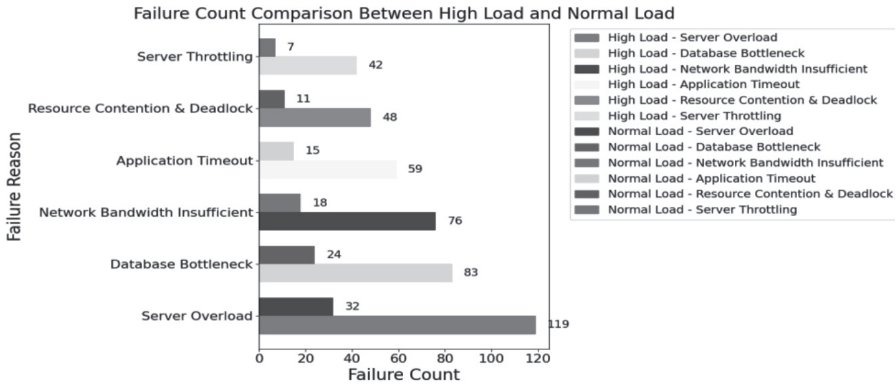

Figure 4 Failed request statistics.

handle most requests well, showing good performance and stability. Therefore, the system's performance under high load is generally superior, and the failure rate is stable at below 5%, indicating that the system has certain elasticity and fault tolerance.

4. CONCLUSIONS

This paper designs an information display interaction system based on visual communication to display advertising information. It uses visual communication technology to optimize the display effect of information and improve the readability and attractiveness of advertising content. At the same time, the system introduces the Transformers model to conduct in-depth modeling and analysis of user behavior data. Based on the output of the Transformers model, it combines the collaborative filtering algorithm to achieve personalized advertising recommendations, thereby giving more accurate advertising information to users which, to a certain extent, provides reference value for the design of future information display interaction systems. However, several shortcomings of this study need to be addressed. First, this study does not take into account the real-time nature of advertising, especially in the current environment where advertising information and user interests are rapidly changing. Second, collaborative filtering can enhance the accuracy of advertising information recommended by the system, but it is easily affected by cold processing and sparsity problems, which may affect the effectiveness of recommendations. Finally, this study focuses on modeling user behavior data, ignoring the impact of factors such as demographic information and social background on the effectiveness of advertising information recommendation. Therefore, future research directions can study methods for real-time system updates. This allows the system to quickly adjust the information displayed when user behavior changes, alleviate the cold start and sparsity problems of collaborative filtering, and increase the modeling dimension by combining information from multiple users.

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