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Research on the Application of Emotion Computing and AI Interaction in Digital Media Advertising and User Response Mechanisms

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Abstract With the development of digital media technology, interactive online advertising has gradually become an emerging form of marketing. By integrating elements such as image, sound, and video, interactive advertisements can attract users' attention and deliver information more efficiently. This study explores the application of affective computing and AI interaction in digital media advertisements and its impact on user response. By constructing an interaction framework centered on user emotion, the role of emotional interaction in enhancing the effect of advertisements is analyzed. In the experiment, the eye movement data of 62 subjects were tracked using an eye-tracker while watching six advertisement videos, and the pop-up and comment data were emotionally analyzed in combination with an emotion lexicon. The results showed that the ad background had a significant effect on the ad effect, with longer first gaze time, yet shorter gaze duration (722ms vs. 467ms) for ads with high contrast backgrounds. In addition, ad position also had a significant effect on ad effectiveness, with ads located in the lower part of the room having a higher probability of being viewed. The study suggests that emotional computing and interactive design can effectively enhance the attractiveness of advertisements and stimulate stronger emotional resonance among users to promote brand communication.

Index Terms Affective computing, AI interaction, digital media advertisement, user response, eye movement experiment, advertisement effect

I. Introduction

With the development of society, people's way of obtaining information has become more and more popular, from the traditional passive to the active nowadays. In the past, information can be obtained through traditional media such as television, newspaper, radio, etc., which all lag behind digital information, especially when obtaining information from newspapers, books and magazines, it is more necessary to think and categorize by oneself, which makes most people lack of initiative and positivity [1]-[4]. But after the emergence of digital media, people put forward higher requirements for advertising design, emphasizing creativity and innovation, but also pay more attention to the connotation of the advertisement, the interactivity of the advertisement form, the digital media advertisements show a wide range of dissemination, low cost, high degree of participation and other advantages by a wide range of applications [5]-[8].

And with the continuous development of artificial intelligence technology, the application of emotional computing and AI interaction design in digital media advertising will provide users with more efficient and intelligent human-computer interaction experience [9], [10]. Affective computing refers to the ability to use computer technology to analyze, recognize and express human emotions and emotional changes, which can enhance the intelligence and effectiveness of human-computer interaction in digital media advertising [11]-[13]. AI interaction design, on the other hand, is a product of combining affective computing with interaction design, aiming to create a more accurate, friendly and natural human-computer interaction experience [14], [15].

The core of this study is to explore how affective computing and AI interaction can be effectively applied in digital media advertisements, and to further explore their impact on user response mechanisms. The study firstly, starts from the design of interactive online animation advertisement and analyzes the advantages of its application in advertising effect. Then, it adopts affective computing and AI interaction to analyze users' emotional feedback, and conducts empirical research on the impact of advertisement design through eye-tracking experimental data, and finally reveals the actual effect of affective computing in advertisements and its specific impact on users' behaviors through data analysis. This process provides advertisers with theoretical and empirical evidence, which helps to optimize advertisement design and improve the emotion-guiding function of advertisements, so as to enhance users' emotional resonance and brand identity.

II. Emotional interaction in digital media advertising

II. A.A user-driven framework for emotional interaction

II. A. 1) Enriching visual effects to enhance the viewing experience

With the development of digital technology, the Internet has brought more space for development in the field of animation. And the emergence of interactive network animation advertisement makes the connection between goods or services and users closer. Interactive network animation advertisement combines animation elements such as image, sound and video with interactive advertisement, so that the information of goods or services can be delivered to users more intuitively. The integration of animation elements undoubtedly makes the sound, picture, color, visual effect, imagination space and other aspects of interactive ads get a qualitative leap. Based on this, interactive network animation ads bring users a rich visual and dynamic experience by virtue of the diversity of composition forms. Interactive network animation ads have more exaggerated visual effects through the changes of shapes, flat and three-dimensional sense of space and depth in the picture. In terms of color, the interactive network animation advertisement adopts abstract concepts and develops associations through color, bringing the associative and synesthetic properties of color to the extreme. In terms of imaginative space, animation gives new life characteristics to inanimate substances and realizes the communication goal of the advertisement through the interaction of characters.

II. A. 2) Enhance interaction to improve the sense of interactive experience

The advantage of interactive network animation advertising is not only reflected in the innovation of advertising form, but also in the change of information dissemination form. It is based on the concept of human-computer interaction using sensors to guide users to interact, so that the original pure visual experience is transformed into a sensory experience. At the same time, in the interactive process, it fully considers the user's sense of experience, incorporating a large number of vivid, humorous, fantasy storylines, which not only achieves the goal of the advertisement to convey information about the goods or services, but also makes the user get psychological pleasure when watching the advertisement. This interactive experience not only reflects the effective communication between the goods or services and the users, but also makes the users feel the corporate culture carried by the products or services.

II. A. 3) Satisfying the emotional needs of users

Interactive network animation advertisement integrates a number of digital technologies and realizes the three-dimensional dissemination of information by virtue of sound, picture, special effects, form and other touchable ways. This way of information dissemination can realize the interaction between goods (services) and users, enterprises and users in a more direct and efficient way. This way allows users to grasp the relevant commodity or service information in the shortest possible time, to understand the characteristics of the commodity or service, so as to find the best, the most suitable related commodities or services. The animation screen is full of fun, fantasy and entertainment, it allows users to get the relevant information of goods or services in a relaxed and pleasant atmosphere, and at the same time choose different goods or services by touching the screen, which greatly enhances the user's interest in interaction. For the design of the interactive process, advertisers should consider the artistry of the animation, the recognizability of the goods or services, the fun of the advertisement and the simplicity of the operation. Due to the excessive pressure of life in modern society, the process of watching interactive web animation ads is actually a short entertainment and stress reduction process. 15-30 seconds of interactive web animation ads coupled with simple human-computer interaction can not only easily achieve the goal of users to understand the product or service information, but also achieve the effect of relaxation and entertainment.

II. B.Affective Computing of Advertising Campaigns in Cognitive and Behavioral Dimensions

II. B. 1) Algorithm design

The advertising effect indicates viewers' “cognitive,” “affective,” and “behavioral” feedback on video advertising content, while the non-advertising effect indicates viewers' attitudes toward non-advertising content, which is more of a feedback on the quality of the author's own video content. The non-advertising effect indicates viewers' attitude towards non-advertising content, which is more of a feedback on the quality of the author's own video content. The quality of non-advertising videos created by video authors depends entirely on the authors' own video creation ability. However, in the long run, the author's creative ability may continue to improve through learning, and in the short run, the performance of the author's creative ability in individual videos has some volatility. In this paper, it is assumed that the author's creative ability is basically unchanged in the short term, and in order to eliminate the volatility of video creative ability in the performance of individual videos, this paper introduces the idea of a moving window to compute the advertising campaign effect based only on the recent n non-advertising videos of a single advertising video. In order to eliminate the fluctuation of the performance of video creation ability in each video, this paper introduces the idea of moving window, and calculates the advertising effect based on the recent n non-advertising videos of a single advertising video. Using the historical data of the mobile window, the average values of non-ad video X_{per} and X_{beh} in the window $\frac{1}{n}\sum_{i=1}^{n}X_{per,i}$ and $\frac{1}{n}\sum_{i=1}^{n}X_{beh,i}$, $X_{per,i}$ and $X_{beh,i}$ represent the values of the i th video "cognition" and "behavior" dimensions in the mobile window, respectively.

$Z_{per,j}$ and $Z_{beh,j}$ represent the advertising effect of the "cognition" and "behavior" of the j advertising video of a single blogger, respectively, and $Y_{per,j}$ and $Y_{beh,j}$ represent the actual video data of the "cognition" and "behavior" of the first j advertising video of a single blogger, respectively, and $Z_{per,j}$ and $Z_{beh,j}$ is:

$$\begin{cases} Z_{per,j} = Y_{per,j} - \frac{1}{n}\sum_{i=1}^{n}X_{per,i} \\ Z_{beh,j} = Y_{beh,j} - \frac{1}{n}\sum_{i=1}^{n}X_{beh,i} \end{cases} \tag{1}$$

In practice, there is often a surge in the number of plays and likes of a blogger's video, which may be due to the fact that the blogger has seized the hotspot information, and the video content is very relevant to the current hotspot content of the society, which ultimately leads to a significant increase in the dissemination effect of the video. However, this does not mean that the blogger's video creation ability has been improved, and the data of this kind of video does not represent the blogger's video creation ability, so such video data is regarded as outlier data. In this paper, we choose the ellipse detection algorithm [16], which is the mainstream in this field, to determine the outliers of multidimensional data.

II. B. 2) Construction of an emotional lexicon

In this paper, we use BosonNLP Sentiment Dictionary as the base dictionary, which is automatically constructed from millions of sentiment annotated data from microblogging, news, forums and other data sources, and it includes many network terms and informal abbreviations, and has a high coverage of non-standardized texts. Seventy negative words are filtered out, and finally the negative sentiment lexicon of this paper is constructed. Degree adverbs were classified hierarchically with reference to the sentiment lexicon of Zhi.com.

In the study of this paper, because the pop-ups and comments contain numerous network terms, and the stuttering lexicon that comes with the Python language cannot realize accurate recognition and segmentation of network terms, it is necessary to create the network neologism dictionary needed in this paper in order to accurately score the text sentiment. In computational linguistics, the Point Mutual Information algorithm is used to measure the word collocation and correlation based on statistical analysis without a reference thesaurus is calculated as follows:

$$PMI(x,y) = \log_2 \frac{P(x,y)}{P(x)P(y)} \tag{2}$$

where $p(x,y)$ denotes the probability that two words word1 and word2 occur together, $p(x)$ is the probability that word1 occurs alone, and $p(y)$ is the probability that word2 occurs alone. If there is a true relationship between word1 and word2, the probability of $p(x,y)$ appearing will be much higher than $p(x)\times p(y)$. In this paper, we choose the words with top 100 PMI values as neologisms after removing the noise words.

Web neologisms need to be scored for their sentiment value after discovery, and this paper uses the Sentiment Orientation Point Mutual Information algorithm (SO-PMI) to calculate the sentiment value of neologisms. The algorithm is to introduce the PMI method into calculating the emotional tendency of words, so as to achieve the purpose of capturing emotional words. The calculation formula is as follows, where word denotes a web neologism, P_{word} denotes a positive word in the sentiment dictionary, and N_{word} denotes a negative word in the sentiment dictionary:

$$SO-PMI(word) = \sum_{P_{word}\in P_{words}} PMI(word, P_{word}) - \sum_{N_{word}\in N_{words}} PMI(word, N_{word}) \tag{3}$$

After calculating the neologism sentiment, the construction of the web neologism lexicon is completed, and the construction of the sentiment lexicon of this paper can be completed by adding it to the base lexicon.

II. B. 3) Text Sentiment Analysis

After completing the processing work such as stuttering and splitting and removing deactivated words of the text data, the sentiment value of the text data can be calculated by utilizing the constructed sentiment dictionary mentioned above. The calculation of the sentiment value of both the pop-up data and the comment data adopts the method of sentiment dictionary.

In this paper, we use Equation (4) to calculate the sentiment value of each advertisement video's pop-up or comment text, and then normalize and take the mean value of the two, so as to get the advertising effect of each advertisement video's "sentiment" dimension, Z_{emo}. In Equation (4), w denotes the average sentiment value of each video pop-up or comment text, k_i is the sentiment value of the i th network term or common language sentiment value, δ_j is the weight of the j th degree adverb modifying the i th sentiment word, -1 is the weight of the negative word, $(-1)^{x_i}\prod_{j=1}^{y_i}\delta_j k_i$ represents that the i th sentiment word is modified by x_i negations and y_i degree words. n is the number of sentiment words in a piece of text, and lenth is the number of ad-related pop-ups or comments in an ad video.

$$W = \frac{1}{lenth}\sum_{n=1}^{lenth}\frac{1}{n}\sum_{i=1}^{n}(-1)^{x_i}\prod_{j=1}^{y_i}\delta_j k_i \quad (4)$$

II. C. Visualization and analysis of pop-up emotions in digital media advertisements

II. C. 1) Pop-up data visualization

Taking an advertising video as a case study, the entertainment series of advertisements creates the effect of positive energy, pleasure, and relaxation, and depending on the theme of the advertisements, the 7-dimensional emotional weight of each advertisement will vary, but the overall tone of the advertisements is focused on positive emotions. In order to better understand the overall emotional tendency of the advertisements selected in this paper, a 7-dimensional emotional radar chart was first drawn, as shown in Figure 1.

The graph shows the distribution of 7-dimensional sentiment of the comments in the advertisement, and the coordinate length of each emotion dimension represents the percentage of the amount of such danmaku data in the total number of effective emotional comments in the ad. Among them, the proportion of positive emotions was 52.14% for "good" and 11.79% for "happy". The proportions of negative emotions were 0.64% for "anger", 11.21% for "sadness", 2.57% for "fear", 19.88% for "evil" and 1.77% for "shock". From the above results, it can be seen that the overall emotion of the five seasons of advertising is more positive, that is, more danmaku data expresses the emotional attitude of users "happy" and "good", but there are still some users who express negative emotions in the process of watching ads, such as "evil" and "sad" emotions, which account for a relatively high proportion.

To summarize, sending pop-ups while watching online media advertisements has become a way of emotional expression for more and more netizens, expressing their positive or negative emotional attitudes and unique insights by sending pop-ups, so that hundreds of millions of users can still speak out at the same time even if they are in different places. In addition, the huge amount of pop-up data, rich emotions, prominent emotional attributes, and ultra-high topicality all show that the majority of users favor entertainment ads, and to a certain extent explain the reason for the outstanding proportion of positive emotions in the entertainment series ads.

In this paper, in order to better understand the emotional changes of the users of online media advertisements, the correlation between the amount of pop-ups and users' emotions is analyzed and compared with the help of the time-pop-up volume line graphs in different time periods, so the time-pop-up volume line graphs based on the data of pop-ups of an advertisement in two phases are shown in Fig. 2. (a) and (b) divide the video playback time into 29s as a unit of time and serve as the horizontal coordinates of the graphs, and the vertical coordinate represents the number of pop-ups sliding across the horizontal screen of the video interface in every 29s, reflecting the dynamic trend of the number of pop-ups over time.

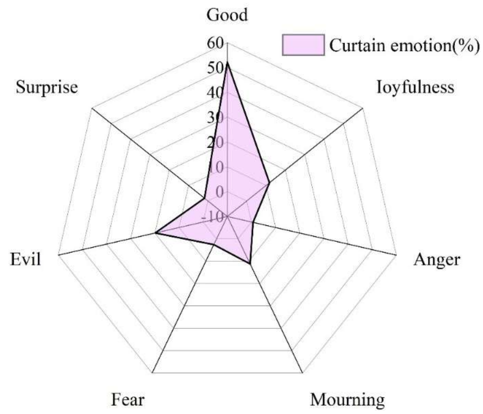
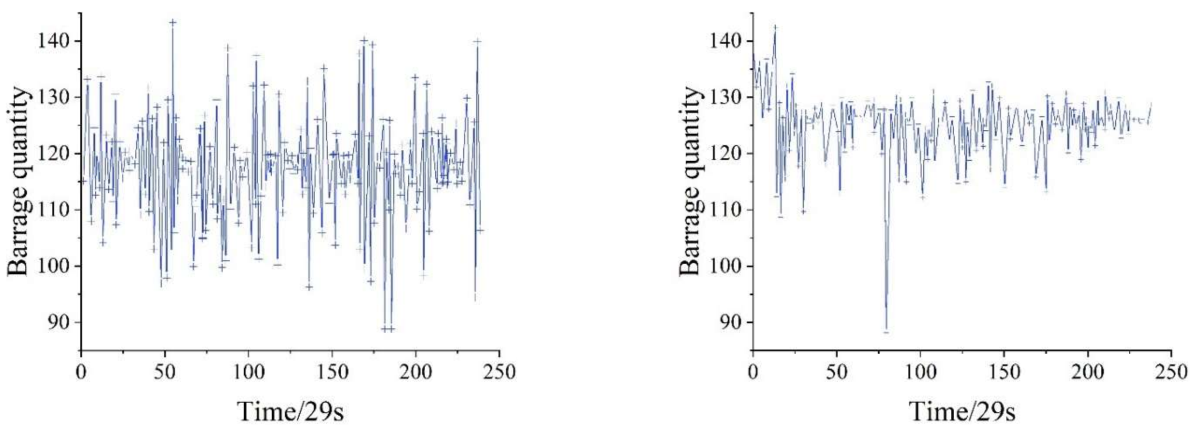


Figure 1: Emotional radar

As can be seen from Figure 2, the number of pop-ups fluctuates significantly as the advertisement continues to play. Among them, in Fig. 2(a), the number of pop-ups was always stabilized in the number range of 97~135 in most periods of the whole period of the advertisement, but there were obvious troughs in the number of pop-ups near 67min44s, 85min9s, 87min5s, 110min17s, and at 25min38s, 38min39s, 48min49s, 77min51s, 78min22s, 80min46s, and 109min44s; in Fig. 2(b), the number of pop-ups was relatively stable in the range of 89~126 in the time period from 6min22s to 106min0s, but there was a significant drop in the amount of pop-ups near 6min47s, 11min32s, and 35min20s. The peak of relative fluctuation of the pop-up quantity appeared near 9min15s, 10min43s, 59min52s, and 60min55s. Combined with the video content and the relevant external stimulus conditions, it can be seen that there are two main reasons for the emergence of the peak, one of which is that the video content in this time period caused strong emotional resonance of the user and directly expressed through the behavior of sending pop-ups; the other reason may be related to the sudden external stimuli, such as the forceful entry of the interstitial advertisement, which caused the user's strong emotions, and the user directly expresses dissatisfaction, resistance and other emotions through the first reaction behavior of sending pop-ups. directly express dissatisfaction, resistance and other emotions.



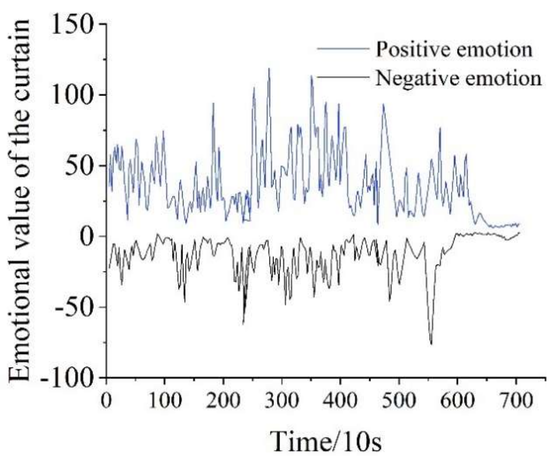
(a) First issue (b) Second phase

Figure 2: Screen review time - quantity line diagram

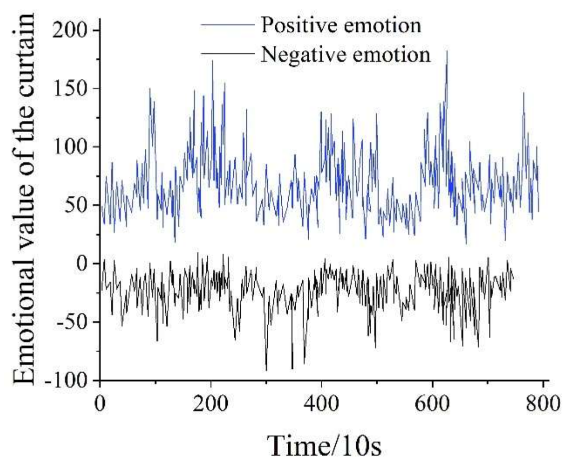
In summary, it can be seen that the number of pop-ups reflects the change of user's emotion from the side, when the user's emotion is high and abundant, the user will express his positive or negative emotion by sending a large number of pop-ups, and complete the real-time interaction and communication with other users; when the user's emotion is low and depressed, the user will choose to send fewer pop-ups or not send pop-ups to hide his emotional state at this time. The above analysis connects the relationship between the amount of pop-ups sent and users' emotions, which provides a new way of thinking to analyze users' emotional changes more accurately.

II. C. 2) Sentiment distribution of pop-up data

In order to understand the emotional changes of users over time when watching online media advertisements, a bi-directional line graph of emotions is plotted based on the pop-up data of digital media advertisements. The graph takes time as the horizontal coordinate axis, and takes every 10s as a time unit, and plots bipolar (positive and negative) emotion line graphs at the same time, as shown in Fig. 3, (a) and (b) are the curves of the pop-up data of the two advertisements, respectively. At the graphical level, the overall fluctuation trend of the positive sentiment value in the following two graphs is significantly higher than the negative sentiment value, and the positive sentiment value in the same time period (i.e., the same point of the horizontal coordinate) is significantly higher than the absolute value of the negative sentiment value in the same position in most cases. However, this situation is not absolute, and does not exclude some time periods where the absolute value of negative sentiment is higher than the value of positive sentiment, such as the position marked by the green circle in the figure above. From the graphical point of view, it can be seen that in general, the combined sentiment of pop-up comments is positive and positive, which is in line with the current situation of the popularity of entertainment advertisements.



(a) First issue



(b) Second phase

Figure 3: The emotional two-way line diagram of the curtain

III. User response mechanisms for digital media advertising under emotional interaction

III. A. Experimental methodology

III. A. 1) Subjects

By advertising for eye movement experimenters on social networking platforms, 70 participants initially signed up for the experiment. Of the 70 original participants, 5 were excluded because the eye calibration failed to meet the required accuracy, and another 3 were excluded due to lack of questionnaire data. The finalized number of subjects for the experiment was therefore 62, of which 37 were female and 25 were male. The age of the subjects ranged from 17 to 46 years, with a mean age of 25 years. All 62 subjects had a visual acuity or corrected visual acuity of 1.0 or higher and were free of eye diseases such as color blindness or color weakness. All subjects were not disturbed during the experiment, and the eye movement and questionnaire data of all subjects were true and valid. Due to the special nature of the eye movement experiment, in order to thank the subjects for their participation in the study, each of them was paid 50 yuan after the completion of the experiment.

III. A. 2) Experimental apparatus and materials

In this study, eye movements of the subjects were tracked using the Eye Tribe eye-tracker.The Eye Tribe eye-tracker has a sampling rate of 60 Hz and a tracking accuracy of approximately 0.5 to 1 degree of viewing angle, which allows for accurate sampling of the subjects' eye movement data.A 17-inch TFT LCD monitor was carried out to be used for presenting the experimental stimuli. Subject eye movement data were analyzed and organized using the Dynamic Video Eye Movement Analysis System developed by Zhang et al. This system tracks the subjects' eye movements for each dynamic object in a video advertisement in order to analyze the participants' eye movements for key elements in the video advertisement.

The advertising materials for this experiment were six video advertisements based on the selection of product elements, including shoes, wine, cell phones, clothes, humidifiers, and razors. To increase the validity of the results, each advertisement material was a commercial video advertisement that had already been circulated in the real world, and the length of the advertisements was consistent with the length of a typical online video advertisement, with each being 30 seconds in length.

III. A. 3) Experimental procedure

Prior to the start of the experiment, the researchers would introduce the overall experimental procedure to the subjects and obtain their signed informed consent. Before watching the video advertisements, each subject was required to pass a nine-point calibration and verification test in order to confirm the subjects' eye condition and ensure the accuracy of the eye movement data collection. After passing the eye movement calibration and test, each subject was required to watch six advertisements, and the AI interaction would track and record their eye movements. After each advertisement was played, the subjects were required to fill out the relevant questionnaire. The duration of the experiment for each subject was approximately 25 minutes, including the process of eye movement calibration, watching the 6 advertisement videos, and filling out the questionnaire for each advertisement.

III. B. Experimental results

The eye movement indexes of each area of interest under different contrast backgrounds are shown in Table 1, and the mean values of the probability of digital media advertisements being seen for high-contrast and low-contrast backgrounds are 29.6% and 31.7%, respectively. The one-way ANOVA test found that the contrast between the background and the advertisement had a significant effect on the first gaze time of the advertisement, $F(1, 18) = 4.573$, $p < 0.05$; the contrast between the background and the advertisement had a significant effect on the gaze time of the advertisement, $F(1, 18) = 11.413$, $p < 0.005$.

The experimental data showed that the probability of a digital media advertisement being seen in a high-contrast background was less than that of a low-contrast background, and the subjects' first gaze time was much higher in a high-contrast page than in a low-contrast page. However, after entering the advertisement area, the subjects' gaze time was longer in the high-contrast page with a mean value of 722 ms, and shorter in the low-contrast page with a mean value of 467 ms. This reflects the inherent repulsion of banner ads, which led to a decrease in the probability of seeing ads that were easy to discriminate in the high-contrast page, and ads that were not easy to discriminate in the low-contrast page, in a sideways manner. Subjects who see an advertisement in a passive situation will choose to leave the advertisement area within a short period of time, while those who are interested in the content of the advertisement will stay in the advertisement area for a longer period of time.

Table 1: Eye movement index among areas of interest under different image contrast background

Background type	High contrast			Low contrast		
	The probability of seeing /%	First time /ms	Fixation duration /ms	The probability of seeing /%	First time /ms	Fixation duration /ms
Figure 1	18	3217	625	15	3582	365
Figure 2	34	2274	825	21	3108	265
Figure 3	18	5697	425	55	1574	605
Figure 4	55	2209	945	28	2193	455
Figure 5	44	3354	635	28	2904	255
Figure 6	41	2469	725	45	1103	505
Figure 7	12	5815	625	26	1537	485
Figure 8	12	9870	1075	26	2613	525
Figure 9	19	3229	565	35	2873	455
Figure 10	43	2958	775	38	2879	755

After one-way ANOVA to obtain the eye movement indexes of each area of interest under different positions, as shown in Table 2, it can be seen that the position has a significant effect on the mean value of the advertisement gaze time, $F(1, 18) = 6.759$, $P < 0.05$; the position has a significant effect on the number of advertisement gaze points, $F(1, 18) = 7.024$, $P < 0.05$; the position has a significant effect on the percentage of people who saw it, $F(1, 18) = 11.112$, $P < 0.005$; location has a significant effect on the time of first gaze, $F(1, 18) = 6.782$, $P < 0.05$.

In the digital media advertising location has a significant effect on advertising effect, the first gaze time of the advertisement located in the lower part is significantly higher than that of the advertisement located in the upper part, so that the top-down process is based on the existing information in the mind to trigger eye movement, and it is the people's active processing of information. Because of the fixed shape of the advertisement, it is easy to distinguish, and the overall reading rate of advertisements placed on the top and the bottom is low due to people's rejection of the advertisements.

Table 2: Eye movement index among areas of interest under different position

Background picture	Position down				Locally			
	Fixed time mean /ms	Number of fixation points	The probability of seeing/%	First time	Fixed time mean /ms	Number of fixation points	The probability of seeing/%	First time
Figure 1	875	12	47	1985	575	10	37	1170
Figure 2	105	2	13	390	641	10	37	1555
Figure 3	495	10	38	3657	720	24	71	911
Figure 4	295	3	15	3100	584	18	55	1624
Figure 5	455	10	37	3723	567	15	57	1508
Figure 6	285	5	21	1563	530	11	41	1210
Figure 7	295	13	45	2679	654	8	35	2145
Figure 8	705	13	45	1590	670	19	61	1550
Figure 9	575	10	40	1855	490	10	38	1510
Figure 10	115	6	10	1780	780	14	75	1422

IV. Conclusion

Through the data analysis of this study, the following conclusions can be drawn:

The contrast of the ad background significantly affects users' attention to the ad. In the high contrast background, the first attention time of the advertisement is longer, but the duration of the attention is shorter, indicating that the user has a strong reaction to the advertisement, but then may leave quickly due to the rejection of the advertisement content. In contrast, ads in low-contrast contexts have shorter first gaze duration but higher user attention to the ads, indicating that users are more willing to delve deeper into the content when viewing the ads.

The position in which an ad is displayed has a significant impact on user response. Ads located in the lower part of the ad page have longer first viewing time and more viewing points than those in the upper part of the page, indicating that users pay more attention to the ads when processing information. Especially in some specific positions, the visualization of the ads is more attractive, thus increasing user engagement.

In summary, the application of affective computing and AI interaction in digital media advertisements effectively enhances the interactivity of advertisements and the emotional resonance of users. By optimizing the background, location and interaction design of advertisements, advertisers can better capture users' attention, improve the communication effect of advertisements, and ultimately lead to users' purchase decisions or brand loyalty.

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