J. COMBIN. MATH. COMBIN. COMPUT. 127a (2025) 8687--8700

Journal of Combinatorial Mathematics and Combinatorial Computing
www.combinatorialpress.com/jcmcc

Research on AIGC advertising strategy based on multi-objective optimisation algorithm

Jingjing Fu[1,✉]

[1] *Art and Media School of Fujian Polytechnic Normal University, Fuzhou, Fujian, 350300, China*

ABSTRACT

The aim of this paper is to improve the advertisement display effect and realize accurate placement in the market. Firstly, the convolutional neural network is used to select the advertisement keywords, and optimize the click rate, conversion rate and so on when the number of iterations reaches a certain value. Next, the established hierarchical analysis model is used to conduct a comprehensive evaluation of online advertisement release forms, and select the advertisement form that best suits the needs of the enterprise and the market environment. The weight of the webpage and the similarity between the center of mass of the webpage and the advertisement are used to calculate the final score, and the advertisements are sorted to achieve the improvement of the display effect and placement accuracy of the advertisements. The final analysis found that for short-term user behavior, the weight of text link ad clusters is as high as 0.66, which can improve the accuracy of ad placement. For long-term user behavior, the multi-objective optimization algorithm can accurately identify and assign high weights when users continue to visit specific web pages, for example, the cluster of web banner ads reaches 0.64. Meanwhile, it can be adapted to different application scenarios, and the weight of text link ads cluster is significantly increased from 0.14 to 0.758 when the freshness factor is increased from 0 to 1. The optimal F1 value of the advertisement delivery effect is 97.24, which is the highest F1 value of AIGC. The AIGC ad placement strategy provides a new method for the intelligent development of the advertising industry.

Keywords: convolutional neural network, multi-objective optimization algorithm, hierarchical analysis model, web page weight, advertisement placement strategy

1. Introduction

In the context of the digital era, the advertising industry is experiencing unprecedented changes, and the optimization of advertising placement strategies has become the key for enterprises to enhance market competitiveness and achieve precision marketing [1]. Traditional advertising placement

✉ Corresponding author.
E-mail address: 18960733940@163.com (J. Fu).
Received 20 February 2024; Revised 15 May 2024; Accepted 20 November 2024; Published Online 15 April 2025.
DOI: 10.61091/jcmcc127a-481

methods, which often rely on manual experience and limited basic data analysis, are difficult to meet the needs of precision marketing in the big data environment. Enterprises need to mine valuable information in the huge ocean of data to develop more accurate and efficient advertisement placement strategies, which has become an urgent problem to be solved [2-3]. Multi-objective optimization algorithms can consider multiple optimization objectives at the same time, such as the click rate, conversion rate, user satisfaction of advertisements, etc. Through algorithm iteration and optimization searching, finding the optimal solution or satisfactory solution that meets all the objectives provides a new way of thinking for optimizing the advertisement placement strategy, which is expected to maximize the advertisement effect. The emergence of AIGC technology is a revolutionary change for the advertising industry, which can promote the intelligence of advertising research, planning, creativity and other processes, and improve the effectiveness and efficiency of advertising [4-5].

In recent years, para scholars have been conducting detailed studies in the field of advertising placement, and the literature [6] has emphasized the importance of advertising placement for supply chain systems, especially in terms of increasing product awareness and sales. Effective advertising placement strategies not only increase product exposure, but also stimulate consumers' willingness to buy. Literature [7] applied game theory and established a delayed differential countermeasure model of supply chain to examine the equilibrium advertising effort, brand goodwill and optimal profit under different cooperation conditions. Finally, it is proposed that by formulating reasonable contract terms, it can ensure that the interests of all parties in the supply chain are balanced in terms of advertising efforts, so as to achieve the overall optimization of the supply chain. Literature [8] represents various factors in the process of advertisement placement, such as user characteristics, advertisement content, and contextual environment, as state directions. Combined with Q-learning algorithm, an advertisement accuracy prediction model is gradually established, and the best advertisement placement action is selected according to the current state using deep reinforcement learning model.

Literature [9] explores the optimal pricing and advertising strategies considering fashion level and goodwill under ODM strategy in fashion supply chain. Differential countermeasure models are constructed for centralization and decentralization. Then a dynamic wholesale price contract is introduced to solve the external coordination problem. A joint optimal pricing and advertising placement strategy is utilized to maximize the overall profit of the fashion supply chain. Literature [10] delves into the initial advertising strategy of the ttl brand through the lens of semiotics, emphasizing the importance of symbols in advertising and how to develop an effective advertising placement strategy through the use of symbols. Symbols play a vital role in advertising, not only as images or words, but also as a bridge of communication between brands and consumers. Advertising conveys information, emotions and values through symbols, thus influencing consumers' attitudes and behaviors. Literature [11] investigated the effect of noise on new product pricing and marketing decisions in a supply chain under a cooperative advertising strategy. Under cooperative advertising strategy, there may be incomplete information among supply chain members. Noise affects the decision quality of all parties in developing advertising strategies, and in order to cope with the uncertainty caused by noise, it is proposed to adjust the advertising budget, change the advertising content or channel in real time according to the market feedback.

The aim of this study is to explore the AIGC advertisement delivery strategy driven by multi-objective optimization algorithm based on the improved convolutional neural network model and combined with the multi-objective particle swarm optimization algorithm to achieve the accurate search and optimization of advertisement keywords. Meanwhile, hierarchical analysis will also be applied to decompose the selection problem into multiple levels and sub-problems, and algorithmic implementation will be used to determine the optimal form of AIGC advertisement delivery. Finally, the user behavioral feature analysis algorithm will be used to analyze the behavioral characteristics of each type of web page and calculate the weight of that type of web page, and the weight and the similarity between the center of mass of that type of web page and the advertisement will be used to calculate the final score, and then the advertisements will be sorted according to this score so as to select suitable advertisements for that type of web page.

2. Multi-objective optimization algorithms in advertising keyword search

2.1. Advertisement keyword selection

In order to better adapt to the needs of advertisement keyword search, the traditional CNN is improved to enhance the search accuracy and provide support for multi-objective optimization. Keyword processing needs to consider its own language characteristics and related features, so it is necessary to improve the CNN. Because the length of keywords varies, it is necessary to limit the length, and according to the actual application scenarios of up to 15, the length of keywords is uniformly set to 15, and the insufficient part is filled with 0. After limiting the length, it is necessary to encode each word in the keyword, i.e., after collecting all the words and de-emphasizing them, encode them sequentially from the first one [12].

The improved convolutional neural network for advertisement keyword selection is shown in Fig. 1, where the corpus is selected and then each encoding is transformed into a word vector using the operation of word embedding. In this paper, word embedding technique is used to convert each encoding into a 300 dimensional word vector. For the keywords that are not in the corpus, random 300-dimensional word vectors are generated. Subsequently, each keyword is converted into a 300*15 matrix, which is used as an input to the convolutional neural network [13]. Through the continuous adjustment of the neural layer weights during the training process, the model is able to select appropriate keywords for advertisers.

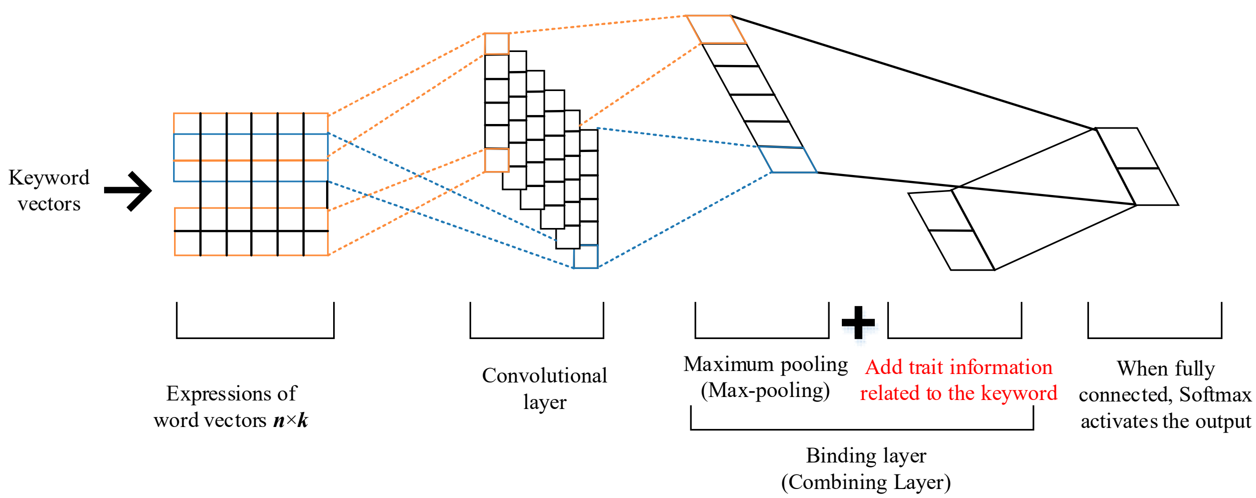

Fig. 1. Improved convolutional neural network for advertisement keyword selection

2.2. Multi-objective particle swarm optimization convolutional neural network

When using CNN for keyword selection, the network structure of CNN is complex and contains many parameters. A multi-objective particle swarm optimization algorithm is introduced to combine with the improved CNN to form a powerful multi-objective optimization system. The system is able to consider multiple optimization objectives simultaneously, such as click rate, conversion rate, etc., so as to realize the comprehensive optimization of advertisement keyword search.

In MOPSO a_1, a_2, a_3, a_4, a_5 is used as the particles which are used to represent the hyperparameters in the CNN, a_1 is the number of filters in C1, a_2 is the number of filters in C2, a_3

is the number of neurons in the hidden layer, a_4 is the probability of loss in the convolutional layer and a_5 is the probability of loss in the fully connected layer [14].

When executing the PSO algorithm, these particles will be randomly initialized. Where, a_1, a_2 and a_3 are between 20 and 150 and a_4 and a_5 are between 0.1 and 0.99. When the imbalance problem needs to be solved, the importance of AUC is higher than the importance of ACC. Therefore, the weight of AUC should be set higher in the adaptation of the particles with the two proposed adaptation functions:

$$Fitness_1 = 1-(2*AUC+ACC) \tag{1}$$

$$Fitness_2 = Time \tag{2}$$

After that these particles will be able to be updated by constant iteration, Fig. 2 shows the multi-objective particle swarm optimization for advertisement keyword search. When the number of iterations reaches a certain value, the optimal second objective that satisfies the range of the first objective is found among the foremost particles, which is the optimal solution, and then the optimal parameters are substituted into the improved CNN to produce the optimal result.

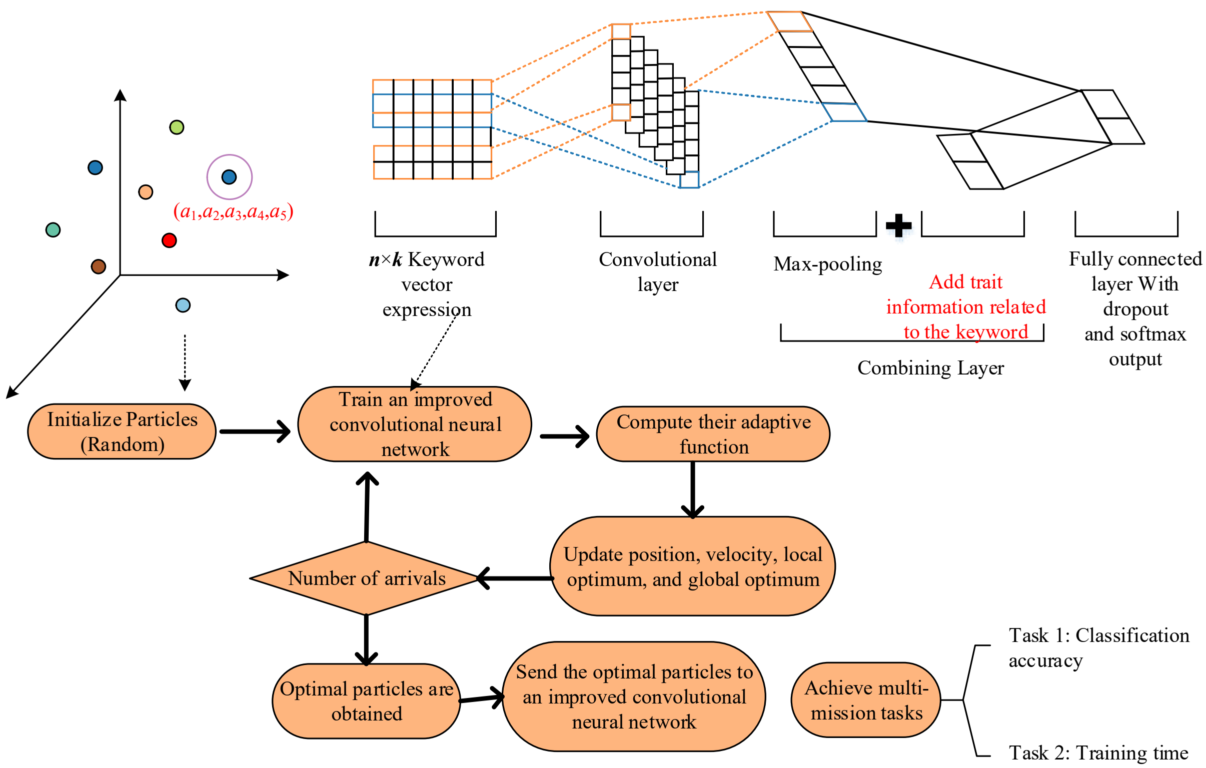

Fig. 2. Multi-objective particle swarm optimization for advertisement keyword searching

3. AIGC content advertisement publishing form

After determining the advertisement keywords, choosing the appropriate form of online advertisement distribution becomes off. Considering the characteristics of AIGC content and the demand for delivery, the hierarchical analysis method is used for the study. The analytic hierarchy process model is established, especially the characteristics of AIGC content are combined with the selection of online advertising publishing forms, and the selection of online advertising publishing forms is decomposed into multiple levels and sub-problems, including the adaptability of network banner advertising, text link advertising, keyword advertising, email advertising and AIGC content, and the optimal online advertising publishing form is determined by using the pairwise comparison method to construct the judgment matrix, the hierarchical single ranking and consistency test, and the hierarchical total ranking and consistency test. A more scientific selection of advertising distribution channels also improves the effectiveness of advertising delivery, especially for AIGC content.

3.1. Hierarchical single ordering and consistency test

3.1.1. Hierarchical single ordering. The research problem is how enterprises can choose the best form of online advertisement release. According to the basic requirements of the guidelines of communication effect and cost of advertisement and the characteristics of evaluation factors, taking the attention rate and the arrival rate as the sub-criteria of communication effect, and choosing 9 indicators such as precision, expressiveness, friendliness, interactivity, effective contact rate, comprehension, credibility, information, and advertisement cost, etc., as the evaluation parameters, i.e., the indicators, respectively. Complete the hierarchization of the problem.

The hierarchical structure reflects the relationships between factors, but each criterion in the criterion level does not necessarily represent the same proportion of the target measure. Analyzing the single ranking of factors at each level relative to a factor at the previous level constitutes a judgment matrix by comparing a series of pairs of factors in a quantitative judgment and writing it out in matrix form. For example, a two-by-two comparison between the attention rate B at the criterion level and C_1, C_2, C_3, C_4 at the indicator level in the model results in a judgment matrix $C = \left(c_{ij}\right)_{4\times4}$.

For the constructed judgment matrices, hierarchical ordering is performed mathematically. Hierarchical single ordering is a measure of the importance of each element of each judgment matrix to its upper level criterion, essentially calculating a weight vector [15]. For example, the four elements C_1, C_2, C_3, C_4 above, for criterion B_1 have a judgment matrix of C. The relative weight $\omega_1, \omega_2, \omega_3, \omega_4$ of C_1, C_2, C_3, C_4 for criterion B_1, written in vector form as $w = \left(\omega_1, \omega_2, \omega_3, \omega_4\right)^T$, is called the weight vector. Regularize each element of the judgment matrix C by column:

$$\overline{c}_{ij} = \frac{c_{ij}}{\sum_{k=1}^{4} c_{kj}} i, j = 1,2,3,4 \tag{3}$$

Find the sum of the elements of the rows in the regularized judgment matrix B, obtained:

$$\overline{\omega}_i = \sum_{j=1}^{4} \overline{c}_{ij} \qquad i = 1,2,3,4 \tag{4}$$

Regularize the resulting column vector, $\overline{w} = \left(\overline{\omega}_1, \overline{\omega}_2, \overline{\omega}_3, \overline{\omega}_4\right)^T$:

$$\omega_i = \frac{\overline{\omega}_i}{\sum_{j=1}^{4} \overline{\omega}_j} i = 1,2,3,4 \tag{5}$$

The obtained weight vector is:

$$w = \left(\omega_1, \omega_2, \omega_3, \omega_4\right)^T \tag{6}$$

3.1.2. Consistency test. Consistency is a measure of the quality of judgments in a judgment matrix. According to matrix theory, for an order n judgment matrix, under the condition of satisfying the full consistency, it has a non-zero maximum characteristic root $\lambda_{\max} = n$, and except for $\lambda_{\max}$, the rest of the characteristics of the heel are all 0, the judgment matrix will satisfy $Bw = \lambda_{\max} w = nw$. However, in the general decision-making problem, the actual value of the judgment element b_{ij} is always a certain deviation from the ideal value, so that it is difficult to satisfy full consistency of the judgment matrix B [16]. At this time there are $\lambda_1 = \lambda_{\max} > n$, the rest of the features with $\lambda_2, \lambda_3, \cdots, \lambda_n$ have the following relationship:

$$\sum_{i=2}^{n} \lambda_i = n - \lambda_{\max} \tag{7}$$

The negative average of the remaining eigenfollowers of the judgment matrix other than the largest eigenfollower can then be used as a measure of the deviation of the judgment matrix from consistency, i.e:

If the largest eigenvalue of $\lambda_{\max}$ is slightly greater than n, and the rest of the eigenvalues are close to zero, which means that CI is close to zero, then the judgment matrix is considered to have satisfactory consistency, and a reasonable conclusion can be drawn. Because of the increase in the order of the matrix, it is difficult to achieve consistency, we need to find a consistency test index for each order of the matrix. The ratio of CI to RI of the same order is called CR. When $CR < 0.1$, the matrix has more satisfactory consistency [17]. Otherwise, the matrix element values need to be reassigned until the conditions are met.

3.2. Hierarchical total ordering and its consistency test

Hierarchical total sorting is the calculation of the single sorting results of all levels in the same hierarchy, which results in the sorting weights of all elements in this hierarchy for the highest level. For example, if the total sorting weights of all elements of the guideline level B_1, B_2, B_3 are b_1, b_2, b_3, and all elements of the indicator level $C_1, C_2, \cdots, C_9$, the corresponding single sorting result of $B_i (i = 1,2,3)$ is $c_{1i}, c_{2i}, \cdots, c_{9i}$. If C_j is not related to B_i, the total sorting of the level $c_{ji} = 0$ needs to carry out a consistency test, and the consistency index of the total sorting is CI:

$$CI = \sum_{i=1}^{3} b_i (CI)_i \tag{8}$$

where $(CI)_i$ is the consistency test metric for each judgment matrix in level C corresponding to B_i. The total hierarchical ordering needs to be tested for consistency, using the total hierarchical ordering of RI to CR to repair. Finally, when $CR \le 0.1$, the result of hierarchical total sorting satisfies the consistency, otherwise the judgment matrix needs to be adjusted until the condition is satisfied. The formulas for RI and CR are as follows:

$$RI = \sum_{i=1}^{3} b_i (RI)_i \tag{9}$$

$$CR = \frac{CI}{RI} = \frac{\sum_{i=1}^{3} b_i (CI)_i}{\sum_{i=1}^{3} b_i (RI)_i} \tag{10}$$

Taking the product promotion as the advertising goal and selecting four advertising forms: web banner ads, text link ads, keyword ads and e-mail ads, the hierarchical stepwise structure of the four advertising form selection problem is shown in Figure 3. The first layer has the total objective, the best advertisement release form. The second layer has two criteria, communication effect and advertising cost, and since they are two criteria, there is no need to establish a judgment matrix, and the weights can be judged directly based on experience. The third level has only two criteria related to communication effect, attention rate and reach rate. Again, no judgment matrix is needed. The fourth layer is the indicator layer, in which the four indicators of precision, expressiveness, friendliness, and interactivity related to the attention rate criterion need to establish judgment matrices, and the four indicators of effective contact rate, comprehension, credibility, and informativeness related to the arrival rate criterion need to establish judgment matrices [18]. The fifth layer is four programs, all of which require the establishment of judgment matrices, except for quantitative data advertising costs, which can be directly calculated weights.

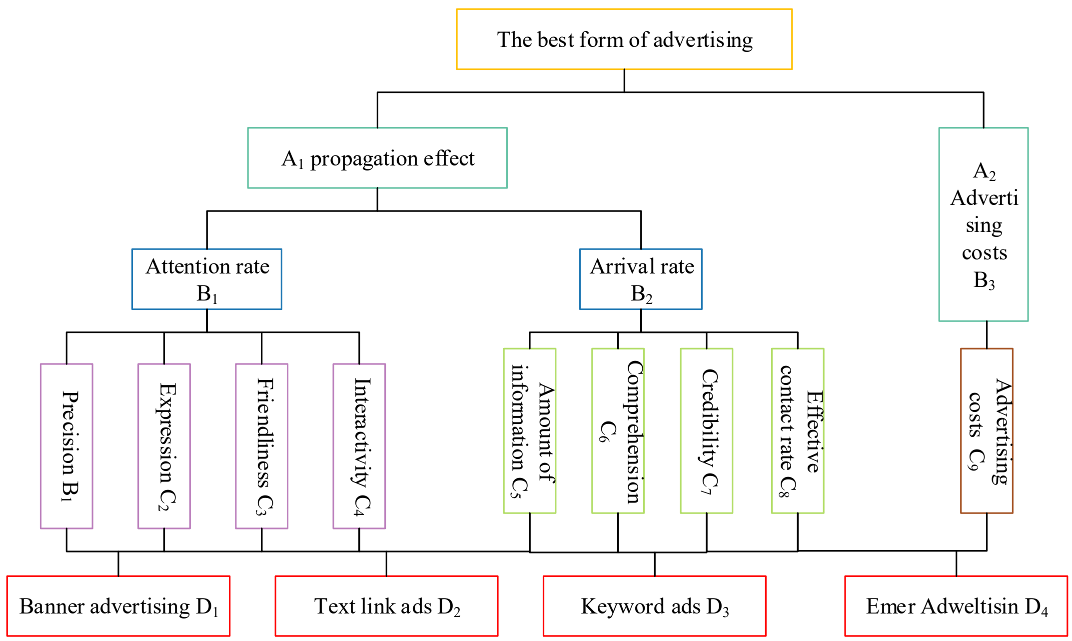

Fig. 3. Hierarchical recursive structure of the four ad format selection problems

4. AIGC Behavioral Targeted Advertising Strategy Implementation

After determining the advertisement keywords and release forms, it becomes crucial to realize AIGC behaviorally directed advertisement placement, and the implementation of AIGC behaviorally directed advertisement placement strategy is shown in Figure 4. By calculating the weights of web pages and the similarity with advertisements, the web pages are initially screened. Then the advertisements are sorted according to the scores to ensure that high-quality advertisements can be displayed to users first.

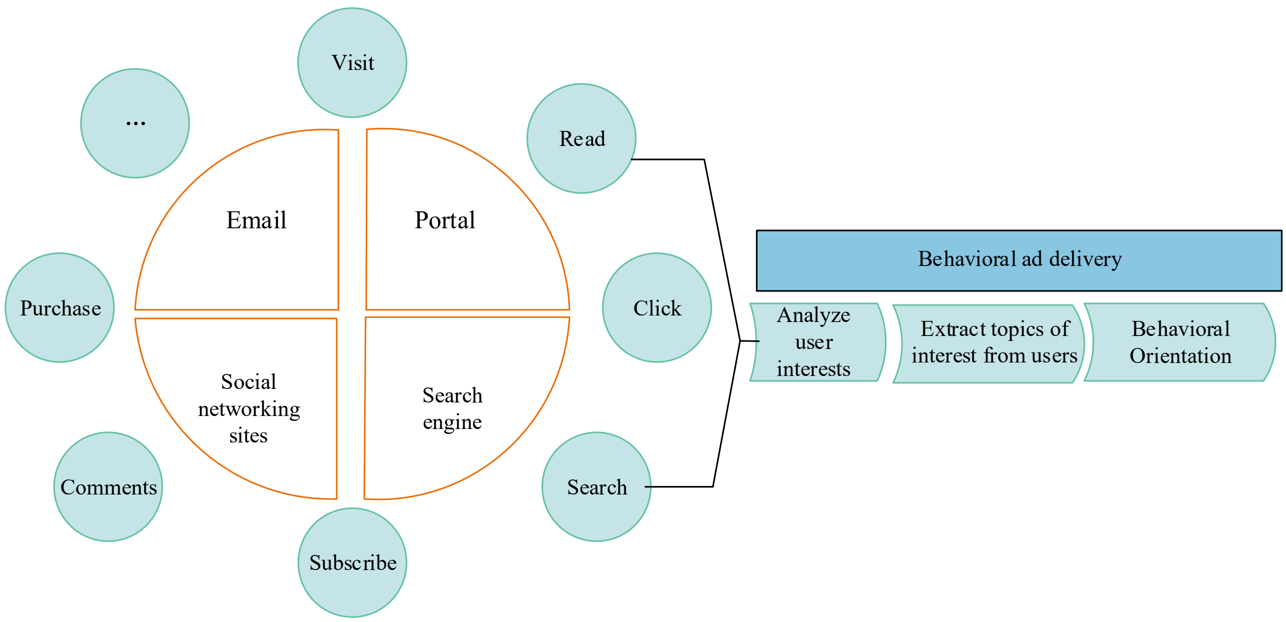

Fig. 4. AIGC behavioral targeted ad placement strategy implementation

4.1. Calculate web page weights and similarity to advertisements

A cluster is considered to reflect a user's behavioral characteristics only if the number of web pages in the cluster reaches a certain value as a proportion of the total number of web pages in the tracking window, and the critical value of this proportion is defined as the behavioral factor, which is expressed as ξ. Therefore, only when the number of web pages in a cluster is greater than $\xi \times m$ is it considered to be a valid cluster that reflects the user's behavioral characteristics, and when it is less than this value, it is considered to be a noisy cluster. For web page clusters reflecting short-term behavioral characteristics of users, the most important factor is the user's access time, the web pages in the cluster are very new indicating that they are of recent interest to the user, and therefore the importance is high, in order to measure the degree of newness of the behavioral characteristics reflected by the web page clusters, it is necessary to define the concept of behavioral freshness, the behavioral freshness is the average access time of the web pages in the valid clusters after the normalization and is denoted by W_f [19]. The average access time $E(t)$ of an effective cluster can be calculated using the following formula:

$$E(t) = \frac{1}{n}\sum_{i=1}^{n} t_i \tag{11}$$

The average access time of all valid clusters constitutes a vector $\vec{V}_e = \left(E_1(t), E_2(t), \cdots, E_k(t)\right)$, where k is the number of valid clusters, so the behavioral freshness W_f of the valid clusters can be calculated using the following equation:

$$W_f = \frac{E(t)}{\left\|\vec{V}_e\right\|_2} = \frac{1}{n\left\|\vec{V}_e\right\|_2}\sum_{i=1}^{n} t_i \tag{12}$$

For clusters of web pages that reflect the long-term behavioral characteristics of users, the most important factor is the degree of dispersion of the web pages; the more widely distributed the web pages in the cluster, the more likely it is that the user will pay attention to the topic at any given moment, and therefore the higher the importance, and in order to measure the degree of this dispersion it is necessary to define the concept of behavioral dispersion.

Behavioral dispersion is the mean squared deviation of the access times of web pages normalized to the effective clusters, denoted by W_d. The mean squared deviation of web page access times can be calculated using the following formula:

$$\sigma(t)=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(t_i-E(t)\right)^2} \tag{13}$$

The mean squared deviation of the access times of all valid clustered web pages constitutes a vector $\vec{V}_d=\left(\sigma_1(t),\cdots,\sigma_k(t)\right)$, so the behavioral dispersion W of the valid clusters can be computed using the following equation:

$$W_d=\frac{\sigma(t)}{\left\|\vec{V}_A\right\|}=\frac{1}{\left\|\vec{V}_A\right\|},\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(t_t-E(t)\right)^2} \tag{14}$$

The final weight W_u of an effective cluster is determined by a combination of the behavioral freshness and dispersion of that cluster. In order to measure the importance of behavioral freshness in the final weight the concept of freshness factor needs to be defined.

4.2. Ranking ads based on scores

The freshness factor is the percentage of behavioral freshness in the final weights and is denoted by λ. Thus W_u can be calculated using the following formula:

$$W_u=\lambda\times\frac{E(t)}{\left\|\vec{V}_e\right\|_2}+(1-\lambda)\frac{1}{\left\|\vec{V}_d\right\|_2}\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(t_i-E(t)\right)^2} \tag{15}$$

In the formula, when $\lambda=0$ means only focusing on the long-term behavioral characteristics of the user, when $\lambda=1$ means only focusing on the short-term behavioral characteristics of the user, and when $0<\lambda<1$ means considering both behavioral characteristics of the user [20]. The final score of the advertisement can be calculated by the following equation:

$$score_{ij}=W_u\cdot\sin\left(d_{QEj},a_k\right) \tag{16}$$

The ads are ranked according to this score from highest to lowest and the ads suitable for that user are selected.

5. Empirical analysis of advertisement placement

5.1. Influence of User Behavior on Ad Placement

5.1.1. Impact of short-term behavior. User behavior is the core consideration in the development of advertising strategy. The short-term and long-term behaviors of users reflect their immediate needs and long-term preferences, respectively, and these behavioral patterns directly determine the reception and effect of advertisements.

Figure 5 shows the effect of short-term user behavior on advertisement placement, when the duration of user behavior is less than 6, the weights of the web clusters about web banner ads, keyword ads, and email ads do not change much. Only at 3 there is a slight change, while the weight of the web clusters of text link advertisements is not available, this is because at this time the number of text link advertisements is less than the critical value of 6 for effective web clusters, which is filtered out as noise clusters. While at 3 a web page about web banner ads exited the tracking window causing the behavioral freshness W of the web banner ads web clusters to become larger thus making the final weight larger. When the duration of user behavior is 6, the text link advertisement cluster becomes effective and since the text link advertisements are newly accessed, the behavioral freshness of this cluster is high resulting in a high final weight of 0.66, while the weights of other web clusters are reduced accordingly. When the duration of user behavior increases, at 15 minutes, the weights of the clusters are stable, with the text link ads cluster having a weight of 0.68, while the banner ads cluster has a weight of 0.38, the keyword ads cluster has a weight of 0.48, and the email ads cluster has a weight of 0.47. When a user visits a certain number of consecutive web pages about a certain topic, the weights of the topic ads become very high. When users visit a certain number of web pages about a certain topic consecutively, the weight of the topic advertisement will become very high, so the advertisement about the topic will be given a higher priority when placing advertisements, and the proposed method is able to effectively mine the short-term behavior of users and place advertisements accordingly.

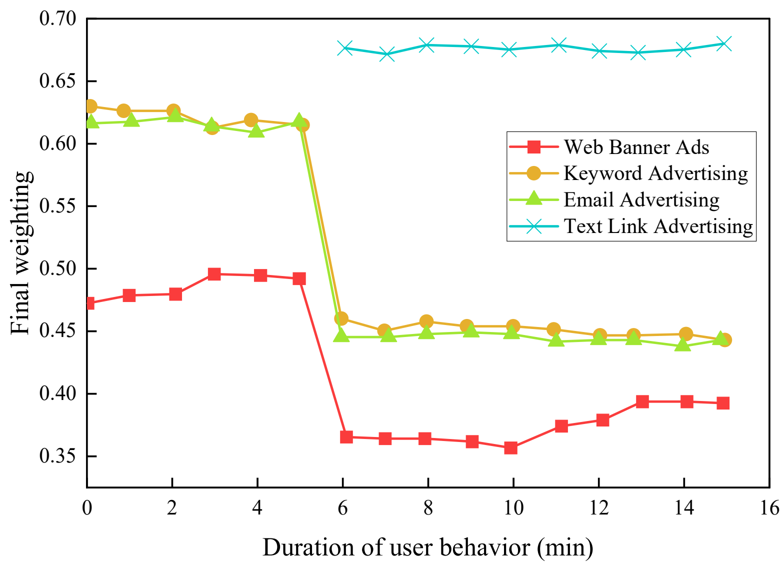

Fig. 5. Impact of short-term user behavior on ad placement

5.1.2. Impact of long-term behavior. Setting λ to 0 at this point the final weight of the web page clusters is only determined by the behavioral discretization, so that web page topics that are frequently visited by users have a higher priority. Figure 6 shows the impact of users' long-term behavior on advertisement placement, users frequently visit web pages about web banner ads, keyword ads, and email ads. Web banner ads are the most widely distributed web pages with a weight of 0.64, keyword ads with a weight of 0.57, and email ads with a weight of 0.52 it is inferred that the user may be interested in web banner ads, and therefore ads related to web banner ads should be placed. When users continue to visit text link ads, text link ad clusters change from noisy clusters to effective clusters, and the weight gradually increases, this is due to the fact that in a specific situation, users frequently click on a text link ad because of a specific interest or need, thus showing the characteristics of concentrated visits, so the behavior of text link ad clusters has a very low degree of dispersion resulting in a very low final weight, and the weight at time point 15 is 0.14, much smaller than the other three clusters which are widely distributed. It can be seen that the method in this paper can effectively mine the webpage clusters reflecting users' long-term behaviors and place advertisements related to them.

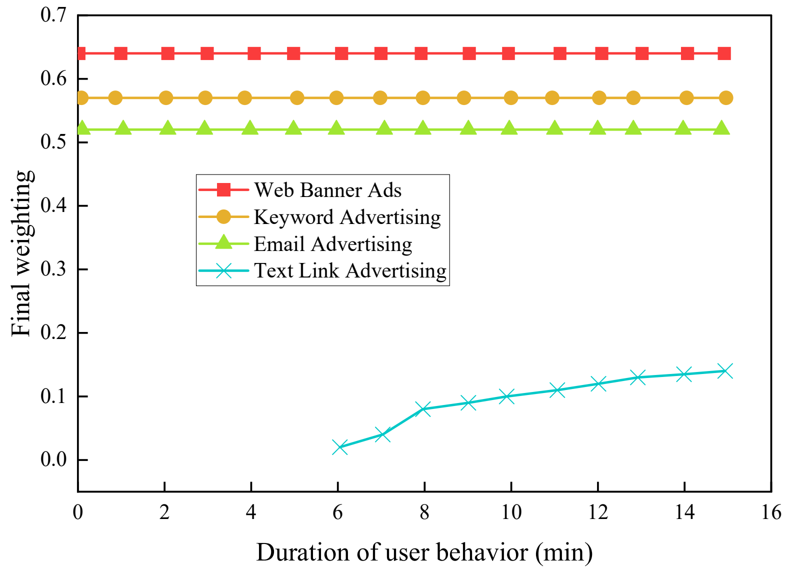

Fig. 6. Impact of long-term user behavior on ad placement

5.2. *Effect of Fresh Factor Values on Ad Placement*

The freshness factor λ measures the importance of behavioral freshness in the final weights, and the effect of freshness factor in on ad placement is shown in Figure 7. When the freshness factor λ gradually increases from 0 with 1, it causes the weight of the text link advertisement cluster reflecting the user's short-term behavior to become larger, when the freshness factor λ is 0.1, the weight of the text link advertisement cluster is 0.167, and the weight of the text link advertisement cluster when the freshness factor λ is 1, the weight of the text link advertisement cluster is 0.758. The weight of the web banner advertisement, keyword advertisement, and email advertisement webpage cluster reflecting the user's long-term behavior gradually decreases. It can be seen that the behavioral targeted advertisement placement algorithm can adjust the weights of users' short-term and long-term behaviors and place appropriate advertisements accordingly to specific applications.

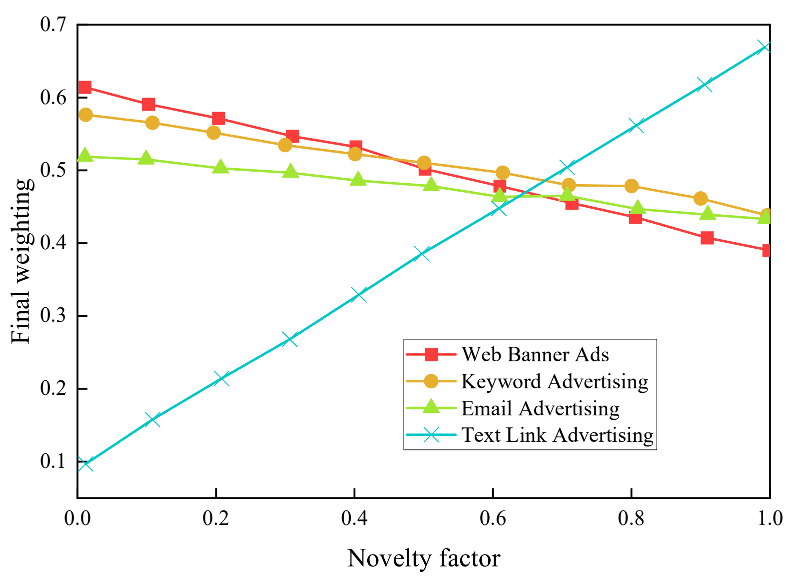

Fig. 7. Impact of Fresh Factor Entry on Ad Placement

5.3. *Effectiveness of advertising*

F1 value is a comprehensive indicator to measure the effectiveness of advertisement placement, combining the performance of both accuracy and coverage of the advertisement. By calculating the F1 value to evaluate the overall effect of advertisement placement, we understand the actual influence of advertisement in the target audience. The comparison results of F1 value of advertisement placement effect are shown in Figure 8, and the multi-objective optimization algorithm in this paper has obvious advantages over other methods. As the number of features continues to increase, the F1 values of the single-objective optimization algorithm, logistic regression, and random forest show a slow decrease, while the F values of the random forest algorithm decrease faster. Considering only one optimization objective click-through rate maximization to optimize the ad placement strategy, particle swarm optimization algorithm is used. The F1 value of the single objective optimization algorithm is 76.32 when the number of features is 100. Logistic regression model to predict the likelihood of advertisement click or conversion, and based on these prediction results for advertisement placement, the logistic regression algorithm F-value is 71.08 when the number of features is 100.Random forest algorithm is used to construct the advertisement effect prediction model, and then optimize the advertisement placement strategy, and the random forest algorithm F1-value is 57.69 when the number of features is 100. Gradient boosting decision tree algorithm to train the prediction model of advertising clicks or conversions to guide advertising, gradient boosting decision tree along with no continuous downward trend, but the F1 value is in the range of 75 intervals, not as good as this paper's method. Multi-objective optimization algorithm to solve synonyms, as well as can be based on the user's actual needs to more accurate advertising. When the number of features is 100, the F1 value of this paper's method is 97.24, and the proposed strategy has excellent performance in advertising effect performance, with effectiveness and advantages.

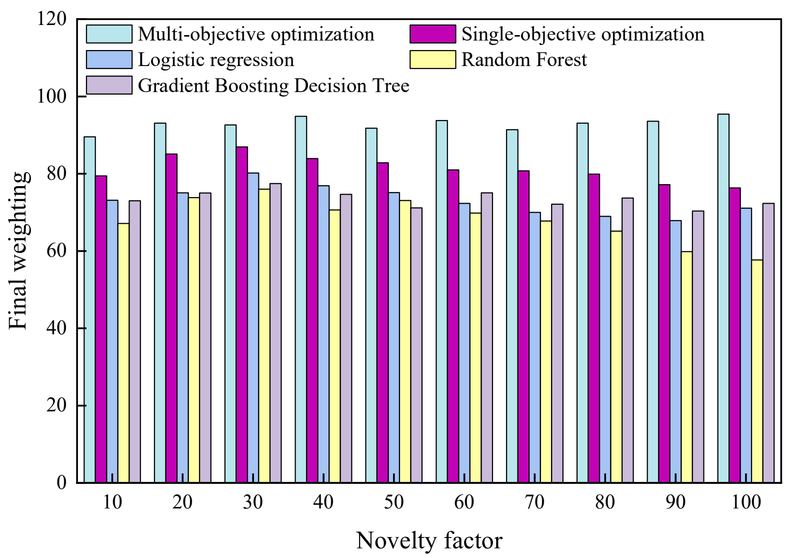

Fig. 8. Comparison result of F1 value of advertisement placement effect

6. Conclusion

The purpose of this paper is to explore how to combine the multi-objective optimization algorithm and AIGC technology to construct an efficient advertisement placement strategy. Through the multi-objective particle swarm optimization algorithm, the accuracy and efficiency of advertisement keyword search are improved. The judgment matrix is constructed through the pairwise comparison method, and the hierarchical single sorting and consistency test, as well as the hierarchical total sorting and its consistency test are performed to provide a basis for the scientific decision-making of the online advertisement release form. Based on the AIGC technology, the weights of the web clusters reflecting user behavioral characteristics are calculated, and efficient behavioral targeting advertisement placement is carried out through accurate user profiling and intelligent placement mechanism, so as to improve the conversion rate of the advertisements and user experience. The results show that the method in this paper can effectively mine the short-term behavior of users and place the corresponding advertisements. When the duration of user behavior is 15 minutes, the weight of text link ad clusters is as high as 0.68, reflecting the keen capture of short-term behavior. Similarly long-term behaviors also have excellent results, and the web banner advertisement web page cluster obtains a high weight of 0.64 due to its wide distribution, indicating that the method can accurately identify and prioritize advertisements with long-term user preferences. When the number of features is 100, this paper's method has achieved an F1 value of 97.24 for the accuracy and coverage of advertisements, which shows remarkable results in practical applications. It is expected that by combining the multi-objective optimization algorithm and AIGC content to explore a new advertisement placement strategy to maximize the advertising effect and provide strong support for enterprises to enhance their market competitiveness.

References

[1] Singh, A., Sajeesh, S., & Bhardwaj, P. (2024). Whitelisting versus advertising-recovery: Strategies to overcome advertising blocking by consumers. *European Journal of Operational Research*.

[2] Guatteri, G., & Masiero, F. (2024). Stochastic Maximum Principle for optimal advertising models with delay and non-convex control space. *arXiv preprint arXiv:2406.07999*.

[3] Rozumei, S., Nikolaienko, I., & Doliuk, A. (2020). Developing an advertising strategy of new product. *Ekonomıka ta upravlınnâ APK*, *1*(1), 129-140.

[4] Di, J. (2023). Principles of AIGC technology and its application in new media micro-video creation. *Applied Mathematics and Nonlinear Sciences*, *9*(1).

[5] Sands, S., Campbell, C., Ferraro, C., Demsar, V., Rosengren, S., & Farrell, J. (2024). Principles for Advertising Responsibly Using Generative AI. *Organizational Dynamics*, *4*, 1-9.

[6] Yu, H., Yang, W., Xu, N., & Du, Y. (2023). Advertising strategy and contract coordination for a supply chain system: immediate and delayed effects. *Kybernetes*, *52*(1), 235-261.

[7] Xie, B., Li, W., Jiang, P., Han, X., & Qi, L. (2022). Cooperative Advertising Strategy Selection Problem for considering Pricing and Advertising Decisions in a Two-Period Online Supply Chain. *Mathematical Problems in Engineering*, *2022*(1), 8922589.

[8] Liang, H. (2020). A Precision Advertising Strategy Based on Deep Reinforcement Learning. *Ingénierie des Systèmes d'Information*, *25*(3).

[9] Chen, Q., & Xu, Q. (2022). Joint optimal pricing and advertising policies in a fashion supply chain under the ODM strategy considering fashion level and goodwill. *Journal of Combinatorial Optimization*, *43*(5), 1075-1105.

[10] Oh, J. , & Jeon, H. Y. . (2022). Advertisement, the secret hidden in the symbol: focusing on the semiotic analysis of the initial advertising strategy of the ttl brand. *Semiotic Inquiry.*

[11] Taleizadeh, A. A., Cheraghi, Z., Cárdenas-Barrón, L. E., & Noori-Daryan, M. (2021). Studying the effect of noise on pricing and marketing decisions of new products under co-op advertising strategy in supply chains: Game theoretical approaches. *Mathematics*, *9*(11), 1222.

[12] Gharibshah, Z., Zhu, X., Hainline, A., & Conway, M. (2020). Deep learning for user interest and response prediction in online display advertising. *Data Science and Engineering*, *5*(1), 12-26.

[13] Kim, G., Choi, I., Li, Q., & Kim, J. (2021). A CNN-based advertisement recommendation through real-time user face recognition. *Applied Sciences*, *11*(20), 9705.

[14] Tian, C., Xu, H., Lu, T., Jiang, R., & Kuang, Y. (2021). Semantic and trade-off aware location privacy protection in road networks via improved multi-objective particle swarm optimization. *IEEE Access*, *9*, 54264-54275.

[15] Wang, W., & Li, G. (2021). A theoretical analysis of the pricing and advertising strategies with Lévy-walking consumers. *Journal of Theoretical and Applied Electronic Commerce Research*, *16*(6), 2129-2150.

[16] Sharpe, S. (2021). Accounting-based brand scandals and the implications for firm-level advertising spending. *Studies in Business and Economics*, *16*(2), 230-239.

[17] Darley, W. K., & Lim, J. S. (2023). Advertising creativity and its effects: a meta-analysis of the moderating role of modality. *Marketing Letters*, *34*(1), 99-111.

[18] Teeny, J. D., Siev, J. J., Briñol, P., & Petty, R. E. (2021). A review and conceptual framework for understanding personalized matching effects in persuasion. *Journal of Consumer Psychology*, *31*(2), 382-414.

[19] Amigó, E., Giner, F., Gonzalo, J., & Verdejo, F. (2020). On the foundations of similarity in information access. *Information Retrieval Journal*, *23*(3), 216-254.

[20] Chen, Y., Li, S., & Jiang, T. Research on prediction of user advertising recommendation system based on NFM model. *Academic Journal of Computing & Information Science*, *5*(13), 1-6.