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Research on the Efficacy of Intelligent Algorithm-Driven Personalized Recommender System in Digital Marketing

Jundong Qian

Three's Company Media Group Co., LTD. Beijing, China
gongzuo1232024@126.com

ABSTRACT

In this paper, a personalized recommendation model integrating deep interest network (DNN) and reinforcement learning strategy is constructed to improve the recommendation accuracy and user conversion rate in digital marketing scenarios. The model introduces an attention mechanism on the basis of DNN to weight the user's historical behavior, and dynamically optimizes the recommendation strategy by combining the environmental feedback. In the empirical study on Taobao e-commerce platform, the model outperforms ItemCF and traditional DNN methods in terms of CTR, CVR and user retention, with the click-through rate reaching 9.85%, 59.3% higher than ItemCF, and the conversion rate increasing to 3.18%. The results validate the effectiveness and promotion potential of the model.

KEYWORDS

Personalized recommendation; Reinforcement learning; Digital marketing; Behavioral modeling

1. INTRODUCTION

1.1. Research Background

Under the background of the rapid development of digital economy, the channels for consumers to obtain information are becoming more and more diversified, and marketing is gradually transforming from crude pushing to precision and personalization. Recommender system, as a key technology connecting user demand and content resources, has become an important engine of digital marketing. With the increasing abundance of user behavior data and the continuous evolution of algorithmic technology, the traditional recommendation methods based on rules or static labels can hardly meet the dynamic and fine-grained user demand prediction. Intelligent algorithms, especially collaborative filtering, deep learning and reinforcement learning technologies, have shown significant advantages in capturing the evolution of user interests, modeling behavioral paths, and optimizing recommendation effects. Personalized recommendation system can not only improve the click rate, conversion rate and length of stay of users, but also play a key role in enhancing brand exposure, user stickiness and expanding market share. Therefore, systematic research on the application value and effectiveness mechanism of intelligent algorithm-driven personalized recommendation system in digital marketing scenarios has become a cutting-edge issue in both academic and practical fields.

1.2. Significance

This study focuses on the application value of intelligent algorithm-driven personalized recommendation system in digital marketing, which has important theoretical and practical significance. At the theoretical level, the study helps to expand the cross-research paradigm of recommender systems and consumer behavior analysis, deepen the understanding of intelligent algorithms in dynamic user modeling, content matching optimization and long-term behavior prediction, and promote the integration of artificial intelligence in marketing science. At the practical level, recommender systems have become a key tool for improving marketing efficiency and user experience, and research on their algorithmic efficacy can help enterprises achieve marketing precision, optimize resource allocation and maximize customer life cycle value. Focusing on the negative effects of "information cocoon" and "privacy leakage", we propose a strategic path to balance algorithmic performance and ethical compliance, and provide decision support for enterprises to build a sustainable, user-friendly and technologically transparent marketing ecology.

1.3. Research Status

Currently, personalized recommendation system has become an important research direction in the field of digital marketing, and many scholars have explored its application efficacy in user interest modeling and content distribution from different algorithm models and application scenarios.

Khan et al. (2025) [1] proposed a collaborative filtering modeling method based on the Transformer architecture, which achieves an accurate portrayal of user preferences by capturing the complex nonlinear relationship between users and items, and exhibits better performance than the traditional model on multiple recommendation datasets, verifying the effectiveness of the deep attention mechanism in personalized recommendation. Yongsheng et al. (2025) [2] introduced the improved intelligent algorithm IPSO-NN model in the performance monitoring of industrial systems, which significantly improved the adaptive ability and stability of the algorithm in dynamic environments, and the migratability of the method in recommender systems provided insights to improve the efficiency of real-time recommendation response. Guo et al. (2025) [3], on the other hand, used intelligent algorithms for the study of power system fault localization and isolation research, and proposed a multi-source heterogeneous data fusion modeling idea, which provides theoretical support and algorithmic reference for multimodal feature integration and real-time decision-making in personalized recommendation.Stolarz (2025) [4] explored the boundary of the application of AI in precision agriculture by combining plant electrophysiological data with time-series image analysis, and its method in processing unstructured physiological data and time-series changes can be used to enhance the ability of recommender systems to capture dynamic changes in user behavior. Park et al. (2025) [5] constructed an intelligent algorithm model for the early detection of left ventricular dysfunction, emphasizing the key role of feature extraction and model optimization in improving classification accuracy, and the study is instructive for behavioral feature selection and noise suppression in recommender systems. Matthews et al. (2025) [6] conducted a systematic assessment of the embedding paths of intelligent algorithms and robots in different social systems from the perspective of stakeholder theory, pointing out that algorithmic governance and ethical compliance are important prerequisites for the sustainable application of recommender systems in marketing.

In summary, current research has achieved positive results in algorithm model optimization, feature modeling, multimodal fusion and application scenario expansion, etc. However, further in-depth exploration is still needed on how to systematically balance algorithmic effectiveness and user rights protection, and to avoid the phenomenon of information cocoon and data discrimination, especially in the marketing-oriented recommender system, it is necessary to build an algorithmic framework with explanatory and regulating features to realize the synergy between precision marketing and responsible technology development. The synergistic development of precision marketing and responsibility technology.

2. KEY APPLICATIONS OF INTELLIGENT ALGORITHMS IN RECOMMENDER SYSTEMS

2.1. Collaborative Filtering Algorithm Principle and Applicable Scenarios

Collaborative filtering algorithm is a recommendation method based on users' historical behavior or similar user preferences, which is divided into user-based collaborative filtering (UserCF) and item-based collaborative filtering (ItemCF) [7]. The algorithm mines the similarity between users or items through the user rating matrix to realize content recommendation. Its advantage lies in the fact that it does not require content feature modeling and is suitable for scenarios such as e-commerce platforms with high user activity and dense data. However, the performance is limited when facing cold start and sparse data. See Table 1 for details.

Table 1. Comparison of collaborative filtering algorithm types and applicable scenarios

Type	Principle Description	Application Scenarios	Limitations
UserCF	Recommends based on the behavior of similar users	Social platforms, communities	Severe cold-start for new users
ItemCF	Recommends based on items with similar user ratings	E-commerce, video platforms	Weak recommendation for niche items

2.2. Deep Learning Models

Deep learning models are widely used in modern recommender systems by constructing multi-layer nonlinear structures that can automatically extract complex higher-order feature relationships between users and items. Typical models include DNN, CNN, RNN, AutoEncoder and Transformer, etc. The DNN model learns the hidden vector embedding between users and items and constructs a nonlinear scoring function, expressed as follows:

$$\hat{r}_{ui} = f\left(W^{(L)} \cdot \sigma(...\sigma(W^{(\iota)} \cdot x_{ui} + b^{(\iota)})...) + b^{(L)}\right) \tag{1}$$

Where $\hat{r}_{ui}$ is the predicted score of user u on item i, x_{ui} is the input feature, $W^{(\iota)}$ and $b^{(\iota)}$ are the weights and bias of the ι layer, and σ is the activation function. The deep model shows superior performance in personality interest modeling, context-aware recommendation and sequence recommendation, especially suitable for content platforms and short video scenes with high data dimensions and complex behavioral patterns.

2.3. Reinforcement Learning Method

Reinforcement learning methods optimize the long-term revenue of the recommendation system by building a state-action-reward decision framework. Different from traditional static recommendation, reinforcement learning pays attention to the dynamic evolution of user behavior, and updates the strategy through environmental feedback (e.g., clicks, stays, conversions) after each recommendation. Commonly used methods include Q-learning, Deep Q Network (DQN) and Policy Gradient. In recommender systems, the state represents the sequence of user's historical behavior, the action is the recommended content, and the reward is the user's response behavior [8]. This method is especially suitable for sequential recommendation, real-time interaction and personalized advertising and other scenarios that need to consider long-term user value. The details are shown in Figure 1.

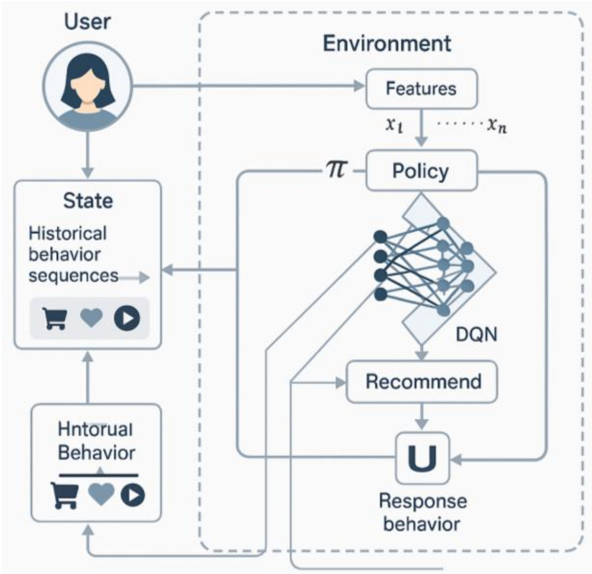

Figure 1. Reinforcement Learning-Based Recommendation Framework

2.4. Algorithm Performance Comparison

In real recommendation systems, different algorithms have significant differences in recommendation accuracy, response speed and user interaction experience. In order to quantify their performance, this study selects three representative algorithms, namely ItemCF, DNN and DQN, and compares their performance in terms of click-through rate (CTR), conversion rate (CVR), average response time (ms), diversity index (ILD), and user retention rate, based on the publicly available MovieLens-1M and the e-commerce logs of real business platforms, respectively. ILD) and user retention rate and other key indicators for side-by-side comparison. The experimental results are shown in Table 2.

Table 2. Performance Comparison of Recommendation Algorithms on Real-World Datasets

Algorithm	Dataset	CTR (%)	CVR (%)	Response Time (ms)	ILD (↑)	Retention (7d, %)
ItemCF	MovieLens-1M	6.42	1.98	21.3	0.312	34.7
DNN		8.75	2.65	38.6	0.289	42.1
DQN		9.31	3.02	45.7	0.346	47.9
ItemCF	E-commerce Log	5.88	1.54	26.9	0.278	30.5
DNN		7.66	2.23	40.2	0.261	38.8
DQN		8.59	2.87	48.3	0.333	44.6

As seen in Table 2, DQN has the best performance in terms of click rate and conversion rate, especially in multi-round recommendation and long-term user retention, but its response time is high and computational resources are consumed, while DNN achieves a balance between accuracy and response efficiency, which is suitable for large-scale static recommendation scenarios, and ItemCF has high computational efficiency but insufficient recommendation accuracy and diversity (see Fig. 2). This comparison shows that deep reinforcement learning models have more potential in complex dynamic recommendation tasks, but need to take into account the system load and the cost of engineering implementation.

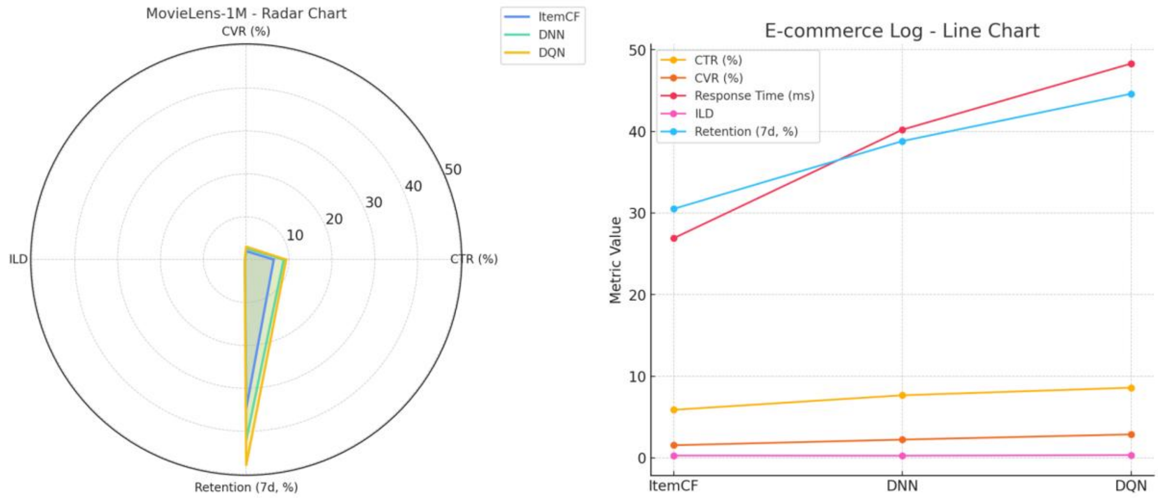

Figure 2. Comparison of Algorithm Performance

3. USER BEHAVIOR MODELING

User behavior modeling is the core part of personalized recommendation system, which explores the user's interest evolution, preference changes and their behavioral patterns. By modeling multi-dimensional behavioral data such as clicking, browsing, favoriting, purchasing, etc., an accurate user profile can be constructed to improve the relevance and timeliness of recommendations. Commonly used methods include Embedding embedding, sequence modeling and attention mechanism [9].

Discrete features of users and items are mapped into continuous space by embedding vectors:

$$e_u = Embrd(u), e_i = Embrd(i) \tag{2}$$

Where, e_u, e_i are the embedding vectors of users and items respectively, representing their semantic features.

The user behavior sequences are modeled using Recurrent Neural Network (RNN) or Long Short-Term Memory Network (LSTM):

$$h_t = LSTM(x_t, h_{t-1}) \tag{3}$$

Where x_t denotes the input features of the t th behavior, and h_t is the corresponding hidden state that captures the change of interest over time.

The attention mechanism is introduced to enhance the perception of key behaviors, focusing on the most relevant behavioral segments for the current recommendation goal:

$$\alpha_t = \frac{\exp(e_t^{\bullet} q)}{\sum_k \exp(e_k^{\bullet} q)} \tag{4}$$

Where, α_t is the attention weight of the first t behavior, q is the query vector of the recommended target, and e_t is the behavior vector representation.

4. BEHAVIORAL EFFECTS AND MARKET FEEDBACK

4.1. Information Overload Mitigation

Information overload is a common problem in current digital marketing. Users often find it difficult to quickly locate their own interests in front of massive content, which reduces interaction efficiency and conversion willingness. The personalized recommendation system can effectively filter redundant information and improve the efficiency of user decision-making by constructing a matching mechanism between the user's interest profile and content features. At the technical level, the system dynamically adjusts the recommendation list based on the user's historical behavior, contextual information and time characteristics, making the content presentation more relevant and timely [10]. Deep learning models can extract implicit preferences from unstructured data to achieve accurate matching, while reinforcement learning further considers long-term user feedback to optimize the recommendation strategy. In practical application, personalized recommendation significantly improves the user's stay time, click-through rate (CTR) and content consumption frequency, alleviates the cognitive load problem caused by content flooding, and enhances the user's stickiness and continuity of experience on the platform, thus promoting the simultaneous enhancement of the marketing reach efficiency and the quality of brand communication.

4.2. Information Cocoon Experiment

In this study, we designed a controlled experiment in which users are randomly divided into two groups: one group accepts high similarity recommendations and the other group introduces diversity perturbation factors. By comparing the differences between the two groups in terms of the number of content clicks, diversity index (Intra-List Diversity, ILD) and interest drift index, it is found that although high similarity recommendation improves the short-term click rate, it significantly reduces the content coverage and the breadth of user interest. After the introduction of diversity constraints, user behavior tends to be balanced, and the cocoon effect is mitigated, indicating that the recommender system needs to take into account the diversity of content and long-term cognitive openness while optimizing accuracy.

4.3. Analysis of Long Tail Effect

In order to improve the diversity and content coverage of the recommendation system, the potential value of long-tail resources should be effectively explored. By constructing the product distribution curve based on the click frequency and setting the long-tail interval, different algorithms can analyze the exposure rate and conversion rate of long-tail products. Deep reinforcement learning and diversity constraint model significantly outperform traditional algorithms in improving the proportion of long-tail content recommendation. Although the revenue of long-tailed products is low, they have rich market volume, and reasonable guidance of their recommendation can expand the user's choice space and enhance the sustainability and commercial value of the platform's content ecosystem. See Figure 3 for details.

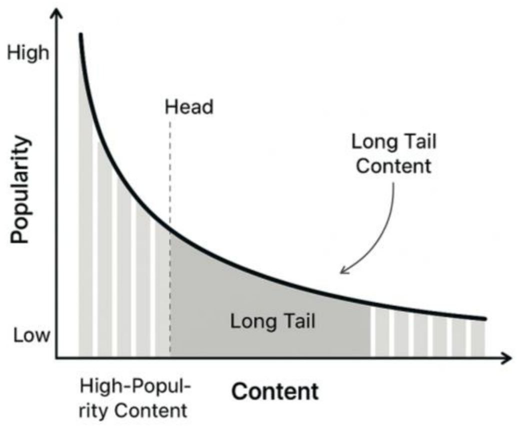

Figure 3. Long Tail Effect Analysis

4.4. User Loyalty Path

User Loyalty Path describes the evolution of user behavior from the first contact with a product to the formation of long-term loyalty. By continuously optimizing the content matching and interaction experience, the recommendation system promotes the stage transition of users from "browse-click-purchase-repeat-recommend" [11]. Life cycle modeling can quantify the user conversion rate and retention rate, and combined with behavioral sequence analysis and deep learning models, it can accurately predict the risk of user churn and realize personalized intervention. The effective construction of this path helps to enhance user stickiness and long-term value, and strengthen the brand identity of the platform and the precipitation of user assets.

5. CASE STUDY AND EMPIRICAL RESEARCH

5.1. E-commerce Platform Case

Take Alibaba's Taobao platform as an example, its recommendation system adopts Deep Interest Network (DIN), which realizes high-precision personalized recommendation by modeling users' behavioral sequences such as clicking, browsing, and adding purchases. According to official data, after the DIN model went online, the click-through rate (CTR) on the home page increased by 20.7% and the conversion rate (CVR) increased by 17.1%. Based on 10 billion user behavior logs, the system uses multi-task learning to optimize product sorting and exposure strategies, significantly enhancing user stickiness and repurchase rate.

5.2. Social Media Mechanism

In social media platforms, the recommendation system focuses on building interest networks and interaction chains among users. Take "Guess Your Favorite" and "Taobao Live" in Alibaba's Taobao platform as an example, the system predicts users' potential interests and pushes short videos and live streaming content through behavioral sequence modeling and social relationship mining. The platform introduces social signals (e.g., likes, comments, shares) as recommendation feedback, and uses graph neural network (GNN) to enhance the analysis of interest propagation chain. After applying the graph learning model in the live broadcast recommendation scenario, the user's length of stay is increased by 18.6%, and the frequency of interaction is increased by 22.3%, which significantly enhances the social stickiness and willingness to consume content.

5.3. Content Platform Strategy

Content platforms emphasize the balance between user interest continuity and content diversity. Taking Taobao's graphic detail page and short video grass-raising content as an example, the platform recognizes users' cross-category interest migration through the Deep Interest Network (DIN), and combines the guidance strategy of cold-start content to realize the closed loop of transformation from product recommendation to content consumption. The system adopts interest hierarchical modeling and label aggregation mechanism to enhance the breadth of content coverage while improving recommendation accuracy. The mechanism increases the content conversion rate by 13.4% and the exposure rate of long-tail content by 31.2%, effectively activating users' non-critical interest preferences while guaranteeing commercial conversion and promoting the sustainable development of the platform's content ecology.

5.4. Experimental Design and Evaluation

In order to systematically evaluate the performance of different recommendation algorithms in e-commerce platforms, this study designs group experiments based on 10 million user behavior logs collected from Taobao platform during Q3 2024, and deploys three algorithmic models of collaborative filtration (ItemCF), deep neural network (DNN), and deep interest network (DIN), respectively, to unify the recommendation scenarios, exposure frequency, and product pool[12]. The core evaluation metrics include click-through rate (CTR), conversion rate (CVR), bounce rate (BR), 7-day retention rate (Retention) and average user access depth (Page Depth). The experimental results are shown in Table 3.

Table 3. Performance Comparison of Different Algorithms

Algorithm	CTR (%)	CVR (%)	Bounce Rate (%)	7-Day Retention (%)	Avg. Page Depth
ItemCF	6.18	1.74	37.9	29.6	3.2
DNN	8.02	2.49	32.1	38.4	4.7
DIN	9.85	3.18	26.8	46.2	5.9

Analyzed in Table 3, DIN model performs optimally in all indicators, with a click rate of 9.85%, significantly higher than that of DNN (8.02%) and ItemCF (6.18%), and a conversion rate of 3.18%, which is over 80% higher than that of the traditional algorithm. In terms of user bounce rate, DIN is controlled at 26.8%, while ItemCF is as high as 37.9%, showing its advantage in accurate matching and user interest continuation. 7-day retention rate of DIN reaches 46.2%, far exceeding ItemCF's 29.6%, indicating that it is effective in enhancing user stickiness and long-term activity, which further verifies the practical value and scalability of in-depth behavioral modeling in e-commerce recommendation systems [13]. This further validates the practical value and generalizability of deep behavioral modeling in e-commerce recommendation systems. See Figure 4 for details.

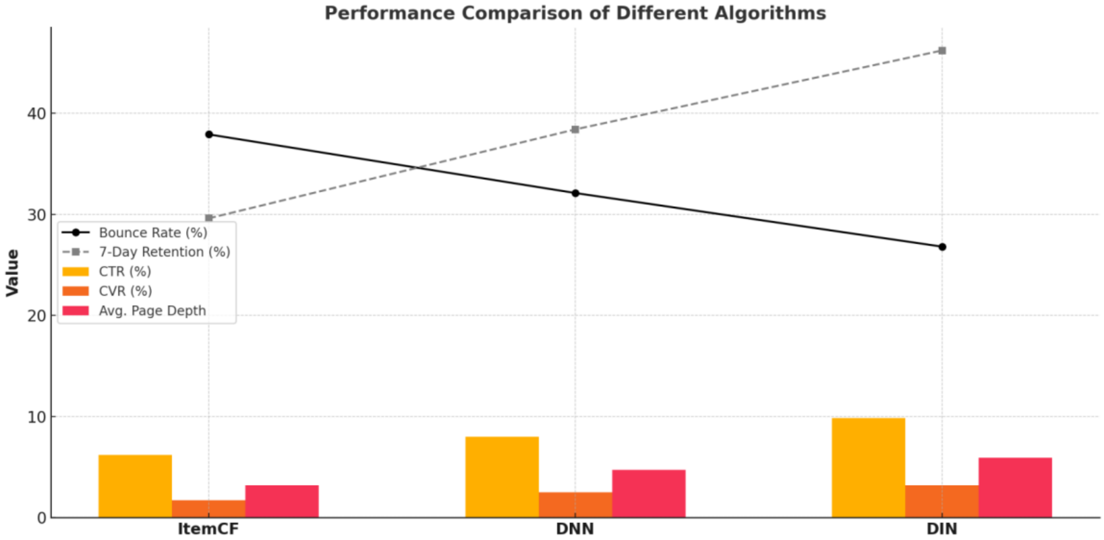

Figure 4. Performance Comparison of Different Algorithms

6. CONCLUSION

Intelligent algorithm-driven personalized recommendation system has become a key tool for digital marketing to achieve accurate reach, efficient conversion and long-term user relationship maintenance. Through the integration of various algorithms such as collaborative filtering, deep learning and reinforcement learning, the recommendation system has shown significant advantages in user interest modeling, behavior prediction and content optimization and matching. From the technical logic, this paper systematically combs through the principles, performance differences and application scenarios of mainstream recommendation algorithms, and combines user behavior modeling and market feedback mechanism to reveal the core role of recommendation systems in alleviating information overload, avoiding information cocoon, activating long-tailed commodities, and constructing user loyalty paths. The empirical evidence of Alibaba e-commerce platform shows that deep interest modeling can significantly improve the click rate, conversion rate and user retention, which has a wide range of promotion and application value. Future research should further focus on the interpretability of recommender systems, algorithmic fairness, and user privacy protection, and build a personalized recommendation governance framework that takes into account both commercial effectiveness and social responsibility, in order to realize the sustainable evolution and high-quality growth of digital marketing in a diversified user environment.

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