Scholar Publishing Group
International Journal of Neural Network
https://doi.org/10.38007/NN.2025.040105
ISSN 2790-2692 Vol. 4, Issue 1: 40-47

Application of AI-driven Personalized Recommendation Technology in E-commerce

Jiangnan Huang

King Graduate School, Graduate student, Monroe University, New Rochelle, 10801, United States

Keywords: AI driven; Personalized recommendation; Electronic commerce; User behavior analysis; Precision marketing

Abstract: In the rapid progress of artificial intelligence technology, AI-driven personalized recommendation system has become a core technology to enhance the user experience of e-commerce platforms and promote sales efficiency. This paper deeply analyzes the application of personalized recommendation system in e-commerce platform, focusing on user behavior data mining, product recommendation and precision marketing. In response to challenges such as data privacy, security risks, recommendation accuracy and diversity conflicts, the optimization path is proposed, including strengthening data encryption and privacy protection, adopting multi-strategy integration to optimize recommendation accuracy, and introducing real-time learning mechanism to cope with changes in user preferences, so as to create a more accurate and reliable recommendation system for e-commerce platforms.

1. Introduction

With the rapid development of e-commerce, personalized recommendation technology has gradually become the core tool to improve user experience and business benefits. Through the in-depth mining of user behavior data by the artificial intelligence recommendation system, the recommendation system can prejudge the user's preferences, so as to launch tailor-made product recommendations, which greatly improves the sales conversion rate. However, personalized recommendation technology still faces challenges in e-commerce platforms such as data privacy, security risks, and the balance between recommendation accuracy and diversity. This paper will deeply discuss the application status, existing problems and optimization path of AI-driven personalized recommendation technology in e-commerce, aiming to provide feasible solutions for the industry.

2. Application of AI-driven personalized recommendation technology in e-commerce

2.1 User behavior analysis and data mining

In AI-driven personalized recommendation system, the analysis of user behavior and data mining play a crucial role. Through the collection and analysis of users' browsing history, purchase history, search behavior and social interaction data on the e-commerce platform, the system can build a detailed user image and gain insight into users' interest points, consumption tendencies and potential needs. Using data mining technology, including but not limited to relational rule, group analysis, joint screening and other algorithms, to explore the deep patterns and trends of user behavior, so as to provide data support for personalized recommendation. The collection of user behavior data is not limited to explicit behaviors, such as clicks and transactions, but also involves implicit behaviors, such as page stay time, mouse movement path, etc. Through comprehensive behavioral data analysis, the recommendation system can grasp user needs more deeply and optimize and adjust in real time.

2.2 Product recommendation and precision marketing

With the help of AI technology, the e-commerce platform has realized the deep integration of commodity promotion and customized marketing, and its core purpose is to deeply explore the preferences and needs of consumers, and then launch products that are highly matched with them, and improve the purchase conversion rate and user experience. By analyzing users' historical behavior data, social network interaction and real-time feedback, the system uses computer algorithms to generate personalized product recommendation lists to ensure that the recommended content is accurately connected with consumer needs. Precision marketing further improves sales by combining recommendation results with marketing strategies. With AI technology, the platform can dynamically adjust marketing strategies, such as advertising, coupon issuance, and limited-time promotions, to meet the specific needs of different consumer groups. AI recommendation systems not only help businesses build accurate Bridges between products and consumers, but also evaluate the effectiveness of marketing campaigns and optimize strategies.

2.3 Architecture and implementation of personalized recommendation system

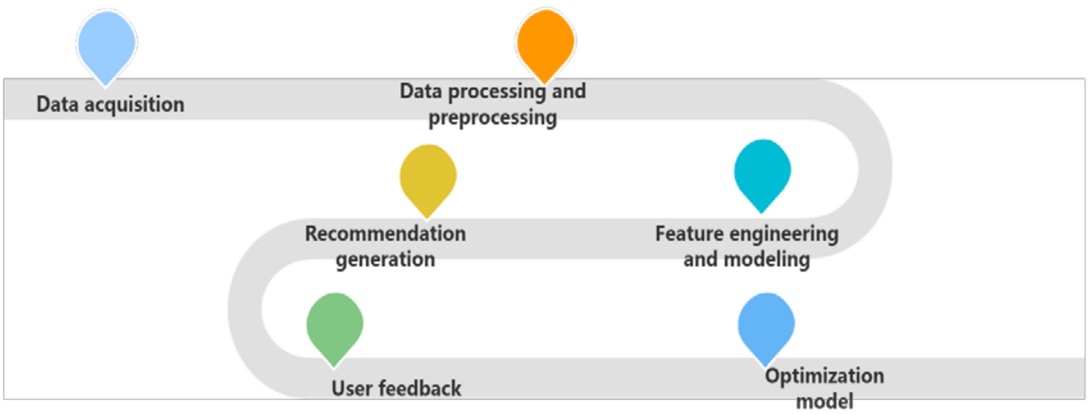

Figure 1. Architecture flow of personalized recommendation system

The implementation of personalized recommendation system covers the key steps such as data acquisition, processing, model training, recommendation generation and feedback optimization. The system uses log capture, API calls or cooperative data sources to collect user behavior information (such as browsing, interaction, search, transaction, etc.) and commodity attribute information , and then preprocesses these data, including data cleaning, weight elimination, filling empty values, and feature extraction, to ensure data quality. In the stage of feature construction and model training, the system uses the recommendation algorithms in computer science such as collaborative filtering, content recommendation and matrix decomposition to build the recommendation model. Collaborative filtering is recommended by the similarity between users or products, and content recommendation is matched by product attributes and user needs. The application of deep learning technology further enhances the recommendation effect and excavates more complex user behavior patterns. The trained model creates a personalized list of recommendations for each user, and the ranking algorithm ensures that the most relevant items are prioritized. The system will also perform real-time optimization based on user interaction and consumption feedback, and dynamically adjust algorithm parameters to improve the accuracy and real-time performance of recommendations. Figure 1 below summarizes the architecture process of a personalized recommendation system:

3. Challenges of AI-driven personalized recommendation technology in e-commerce applications

3.1 Data privacy disclosure and security risks

Data privacy breaches and security risks are one of the core challenges in AI-driven personalized recommendation systems. The system relies on massive amounts of user information, including users' browsing history, purchase history, search habits and personal information, the collection and storage of which puts users' privacy at potential risk of disclosure. Once this information is hacked or improperly leaked, it will not only threaten the security of users' personal information, but also may have a negative impact on the goodwill and business operation of the e-commerce platform, especially in the process of data sharing between different platforms and cooperation with third parties, the risks involved are particularly significant. If the platform fails to implement strong computer security measures or technical encryption, attackers can exploit weaknesses in the interface to steal large amounts of sensitive information. In addition, the opacity or design deficiencies of the system's algorithms may also lead to privacy issues, such as the collection of sensitive information without the explicit consent of the user, which may trigger legal proceedings and a loss of trust. This not only violates the legitimate rights and interests of users, but also may cause the platform to suffer legal liabilities and financial losses.

3.2 Conflict between recommendation accuracy and diversity

In personalized recommendation system, the conflict between recommendation accuracy and diversity is a key problem. The pursuit of accuracy means that the system accurately recommends products that match the user's preferences based on their historical behavior, but this can lead to monotonous and repetitive content, limiting the scope for users to explore new products, creating an "information island effect, reducing the overall experience." To improve the diversity, the system needs to recommend products that are not completely related to the user's historical behavior. Although these products are rich in novelty, they may deviate from the actual point of interest of the user, thus affecting the accuracy of the recommendation and the user's satisfaction. Increased diversity is accompanied by decreased relevance, which can make users feel uncomfortable with recommended products and further affect the conversion rate of users. Therefore, seeking the balance between accuracy and diversity in personalized recommendation system is a difficult problem, which is directly related to the quality of recommendation and the user's feelings. Table 1 below analyzes the conflict between recommendation accuracy and diversity:

Table 1. Conflicts between recommendation accuracy and diversity

Challenge	Recommendation accuracy	Recommendation diversity
Major influence	The single content of the recommendation limits the user's exploration of new products	Recommended products do not match user interests, reducing the conversion rate of purchases
System effect	High precision but lack of innovation, resulting in loss of user interest	Improve exploration at the expense of precision, influencing user decisions
User experience	Users may feel bored and lack novelty	Users may not accept product recommendations that are too irrelevant

As can be seen from Table 1, there is a contradiction in the pursuit of accuracy and diversity in the personalized recommendation system. Too much focus on accuracy can lead to monotonous recommendations, which limits users' opportunities to explore new products. On the contrary, increasing diversity may weaken the correlation between recommendations and user preferences, which will adversely affect user experience and transaction rates.

3.3 Restriction of user preference change and recommendation effect

In the face of personalized recommendation systems, fluctuations in user interest pose a significant challenge. With the passage of time and the changes of the external environment, users' preferences and needs are also constantly changing. If the recommendation system lacks the ability to adjust in time, the accuracy and effectiveness of its recommendation will be affected. Conventional recommendation systems often rely on users' historical behavior data to make prediction analysis, but users' preferences are not static, and old data is likely to deviate from users' current needs, thus reducing experience. In addition, the evolution of user preferences has great instability, and the system must be able to dynamically update the user profile and optimize the recommendation algorithm in time to quickly adapt to these changes. If the system can not identify and adjust in time, it may ignore the new interest content of users, resulting in poor recommendation effect, affecting user satisfaction and platform activity. User dissatisfaction may lead to churn and increase the churn rate.

3.4 Lack of algorithm interpretability and decision-making transparency

In the personalized recommendation system, the lack of interpretability of the algorithm and the lack of transparency of the decision have become prominent problems. Recommendation systems often employ complex machine learning or deep learning models whose black-box nature can make the recommendation process opaque and make it impossible for users to understand why a particular item is being recommended to them. A lack of interpretability can lead to distrust of recommendations, especially when they don't match the user's expectations. At the same time, the opaque decision-making process of the system makes it difficult for the platform to effectively improve the algorithm, and may also cause users to question the platform, thus affecting user stickiness and platform reputation. A lack of transparency can also lead to compliance risks, especially when it comes to data privacy and fairness. Platforms that fail to clearly explain their recommendation logic may be in breach of data protection regulations and therefore face legal risk. Therefore, the lack of transparency and interpretability of the recommendation system will not only affect the user experience, but also hinder the platform's continuous optimization and adjustment of the algorithm. Table 2 below summarizes the challenges and implications of the lack of algorithmic interpretability and decision transparency:

Table 2.Challenges and impacts of algorithm interpretability and lack of decision transparency

Challenge	The interpretability of the algorithm is insufficient	Lack of transparency in decision-making
Major influence	Users cannot understand the process of generating recommendations	Users distrust the recommendation system
System effect	Reduce user acceptance and affect user experience	Limiting the platform's room for improvement can lead to compliance issues
User experience	It is difficult for users to accept recommendations that do not meet their expectations	Users lack trust in recommendations, leading to a decline in platform usage

As can be seen from Table 2, lack of transparency will cause users to distrust recommendation results and affect user experience. At the same time, the platform also faces improvement difficulties and compliance risks, which limits the optimization space of the system.

4. Optimization path of AI-driven personalized recommendation technology in e-commerce applications

4.1 Strengthen data encryption technology and privacy protection mechanism

As personalized recommendation systems increasingly rely on user data, data security and privacy protection become particularly critical. E-commerce platforms need to implement strict computing encryption technology and privacy protection measures in all aspects of data collection, transmission, storage and processing at the computer technology level. In the process of data transmission, the platform must implement end-to-end encryption means, such as the use of AES encryption algorithm, to ensure the security of information in the way of transmission. In the storage process, symmetric encryption and asymmetric encryption algorithms (such as RSA) are combined to encrypt sensitive information, so that data cannot be cracked even if it is attacked. In order to protect user privacy, the platform can use "differential privacy" technology, by adding noise to the data, to avoid the disclosure of users' personal information. The algorithm implements computation and processing in the state of encrypted data, and can execute the recommended algorithm without decryption, thus effectively reducing the possibility of data privacy exposure. In addition, blockchain technology can also enhance data security. Through decentralized data management and smart contracts, the platform can ensure data traceability and transparency, and improve user privacy protection. The relationship between encryption strength and key length can be expressed by the following formula:

$$S = \log_2(2^k) \tag{1}$$

Among them, k Represents the key length of the encryption algorithm, S It is the encryption strength. Increasing the key length can significantly improve the encryption strength and ensure data security. By strengthening data encryption and privacy protection mechanisms, e-commerce platforms can ensure the security of user data, enhance the credibility of the system, and enhance users' trust in the recommendation system.

4.2 Adopt multi-strategy integration to optimize recommendation accuracy and diversity

There are often conflicts between accuracy and diversity in personalized recommendation system. Optimizing the balance between them is the key to improve the recommendation effect. Through multi-strategy integration, this conflict can be effectively reconciled and the overall performance of the recommendation system can be improved. The multi-strategy fusion approach combines different recommendation strategies such as collaborative filtering, content recommendation, and deep learning. Collaborative filtering generates recommendations based on user behavior data by analyzing the interests of similar users, while content recommendations focus on matching based on the characteristics of the product. Combining these two strategies can satisfy users' historical preferences while introducing novel products and increasing the diversity of recommended content. In addition, deep learning technology is able to more accurately capture the complex needs of users, identify potential points of interest through neural network models, and further optimize the accuracy and diversity of recommendations. By weighting the results of different recommendation algorithms, the system can dynamically adjust the tradeoff between accuracy and diversity. According to user behavior feedback and demand changes, the weight of each strategy is adjusted, so that the recommendation results not only meet the interests of users, but also stimulate their exploration of new content, so as to improve the overall experience and satisfaction of users. The recommendation results of multi-strategy integration can be expressed by the following weighted average formula:

$$R\mu = \alpha \cdot R_{CF} + \beta \cdot R_{Content} + \gamma \cdot R_{DL} \tag{2}$$

Among them, $R\mu$ Is the final recommendation, R_{CF} 、 $R_{Content}$ 、 R_{DL} They are the recommendation results of collaborative filtering, content recommendation and deep learning model respectively, α 、 β 、 γ Is the weight of each policy. By adjusting these weights, the accuracy and diversity of recommendations can be optimized to achieve the best recommendation results.

4.3 Introduce real-time learning and adaptive mechanism to cope with changes in user preferences

To meet the challenge of user preference change in personalized recommendation system, real-time learning and adaptive adjustment mechanism become the key strategies to enhance the accuracy of recommendation. Real-time learning can adjust the recommendation model in time according to the latest behavior data of users, so that the system can quickly respond to the change of users' preferences, and avoid the recommendation results from becoming outdated or losing relevance. The adaptive mechanism continuously optimizes algorithm parameters and dynamically adjusts recommendation strategies to ensure that the recommendation system can still provide accurate recommendations when user preferences change. By monitoring the user's interactive data (such as clicking, browsing, purchasing and other behaviors), the system adjusts the recommended content in real time, so as to ensure the real-time and personalized recommendation. In the real-time learning and adaptive mechanism, the following formula can be used to express the relationship between the speed and feedback of model updating:

$$\theta_t = \theta_{t-1} + \eta \cdot \nabla L_t(\theta) \tag{3}$$

Among them, θ_t Is the model parameter of the current moment, θ_{t-1} Is the model parameter of the previous time, η It's the learning rate, $\nabla L_t(\theta)$ Is the gradient of the current moment. By updating parameters in real time, the model can quickly adjust to the latest user behavior and preferences, thereby improving the accuracy and real-time performance of recommendations.

4.4 Improve algorithm interpretability and decision-making transparency

The interpretability of the algorithm and the transparency of the decision in the personalized recommendation system become the important factors of the user's trust and acceptance. Complement or replace complex deep learning models by adopting more interpretable models (such as decision trees, linear regression, etc.) that themselves have a high degree of transparency. In addition, interpretability enhancement methods such as LIME (local linear model interpretation) and Shapley (Shapley Additive interpretation) are introduced, which can analyze the decision-making process of black-box models and help users understand the reasons behind recommendations. In addition, increasing the visual display of the recommendation results, such as showing the impact of each feature on the recommendation results, can further improve the transparency and understandability of the system. As a kind of interpretation mechanism, the core of SHAP value is to quantify the contribution degree of each feature to the decision result, so as to provide a transparent analysis for the prediction decision of the system. The formula is as follows:

$$SHAP(f,x)=\sum_{S\subseteq N/\{i\}}\frac{|S|!(|N|-|S-1)|}{|N|!}[f(S\cup\{i\}-f(S)] \tag{4}$$

Among them, $f(S)$ Representation feature set S The predicted results of, $SHAP(f,x)$ Presentation feature i Contribution to final forecast results. In this way, the system is able to clearly explain the role of each feature in the recommendation results.

5. Conclusion

AI-driven personalized recommendation technology is playing an increasingly important role in e-commerce, which greatly enriches consumers' shopping experience and improves business earnings through accurate user portraits and recommendation algorithms. However, with the development of technology, data privacy, security, recommendation accuracy and other issues have gradually become the focus of attention. In the face of these challenges, e-commerce platforms need to continuously optimize the recommendation system, adopt advanced data encryption and privacy protection technologies, explore the recommendation optimization path of multi-strategy integration, and enhance the transparency and interpretability of the algorithm.

References:

[1] Saver J, Duncan P, Stein J, et al. Abstract WP117: AI-driven Electromagnetic Field Therapy to Reduce Global Disability in Patients with Subacute Ischemic Stroke: Trajectory of Potential Benefit in the EMAGINE 1 Trial. Stroke, 2025, 56(Suppl_1):AWP117-AWP117.

[2] Li Z, Yang X, Zhang D, et al. Exploration of oral microbiota alteration and AI-driven non-invasive hyperspectral imaging for CAD prediction. BMC Cardiovascular Disorders, 2025, 25(1).

[3] Guo H, Guo Z, Liu Z. Personalized Recommendation Model Based on Improved GRU Network in Big Data Environment. J. Electr. Comput. Eng. 2023, 2023:3162220:1-3162220:9.

[4] Cai Y. The Integration of Modern Electronic Technology and E-Commerce: the Driving Force of Innovation Development. Journal of Educational Theory and Management, 2024, 8(2):6-10.

[5] Lazi A, Mili S, Vukmirovi D. The Future of Electronic Commerce in the IoT Environment. Journal of Theoretical & Applied Electronic Commerce Research, 2024, 19(1)

[6] B. Li, "Research on the Spatial Durbin Model Based on Big Data and Machine Learning for Predicting and Evaluating the Carbon Reduction Potential of Clean Energy," 2025

International Conference on Intelligent Communication Networks and Computational Techniques (ICICNCT), Bidar, India, 2025, pp. 1-5.

[7] *Q. Xu, "Implementation of Intelligent Chatbot Model for Social Media Based on the Combination of Retrieval and Generation," 2025 2nd International Conference on Intelligent Algorithms for Computational Intelligence Systems (IACIS), Hassan, India, 2025, pp. 1-7.*

[8] *Y. Zou, "Research on the Construction and Optimization Algorithm of Cybersecurity Knowledge Graphs Combining Open Information Extraction with Graph Convolutional Networks, " 2025 2nd International Conference on Intelligent Algorithms for Computational Intelligence Systems (IACIS), Hassan, India, 2025, pp. 1-5.*

[9] *M. Zhang, "Research on Joint Optimization Algorithm for Image Enhancement and Denoising Based on the Combination of Deep Learning and Variational Models," 2025 International Conference on Intelligent Communication Networks and Computational Techniques (ICICNCT), Bidar, India, 2025, pp. 1-5.*

[10] *W. Han, "Using Spark Streaming Technology to Drive the Real-Time Construction and Improvement of the Credit Rating System for Financial Customers," 2025 International Conference on Intelligent Communication Networks and Computational Techniques (ICICNCT), Bidar, India, 2025, pp. 1-6.*

[11] *J. Huang, "Research on Multi-Model Fusion Machine Learning Demand Intelligent Forecasting System in Cloud Computing Environment," 2025 2nd International Conference on Intelligent Algorithms for Computational Intelligence Systems (IACIS), Hassan, India, 2025, pp. 1-7.*

[12] *J. Huang, "Performance Evaluation Index System and Engineering Best Practice of Production-Level Time Series Machine Learning System, " 2025 International Conference on Intelligent Communication Networks and Computational Techniques (ICICNCT), Bidar, India,*

[13] *X. Liu, "Research on User Preference Modeling and Dynamic Evolution Based on Multimodal Sequence Data," 2025 2nd International Conference on Intelligent Algorithms for Computational Intelligence Systems (IACIS), Hassan, India, 2025, pp. 1-7.*

[14] *D. Shen, "Complex Pattern Recognition and Clinical Application of Artificial Intelligence in Medical Imaging Diagnosis," 2025 International Conference on Intelligent Communication Networks and Computational Techniques (ICICNCT), Bidar, India, 2025, pp. 1-8.*

[15] *Q. Hu, "Research on Dynamic Identification and Prediction Model of Tax Fraud Based on Deep Learning," 2025 2nd International Conference on Intelligent Algorithms for Computational Intelligence Systems (IACIS), Hassan, India, 2025, pp. 1-6.*

[16] *Chen M. Research on Automated Risk Detection Methods in Machine Learning Integrating Privacy Computing. 2025.*

[17] *Ding, J. (2025). Research On CODP Localization Decision Model Of Automotive Supply Chain Based On Delayed Manufacturing Strategy. arXiv preprint arXiv:2511. 05899.*

[18] *Wu Y. Software Engineering Practice of Microservice Architecture in Full Stack Development: From Architecture Design to Performance Optimization. 2025.*

[19] *Wu Y. Optimization of Generative AI Intelligent Interaction System Based on Adversarial Attack Defense and Content Controllable Generation. 2025.*

[20] *Sun J. Quantile Regression Study on the Impact of Investor Sentiment on Financial Credit from the Perspective of Behavioral Finance. 2025.*