Proceedings of CONF-CDS 2026 Symposuim: Data-Centric AI Security: Securing Models, Learning Agents, and Autonomous Systems
DOI: 10.54254/2755-2721/2026.CH34650

Application Effect of AI Recommendation Algorithm in E-commerce Platform Based on User Behavior Data

Ruiyang Wang

School of Data Science, Zhejiang University of Finance & Economics, Hangzhou, China
wwwrrryyy30@163.cm

Abstract. Due to information overload in e-commerce, users often suffer from low decision-making efficiency. AI recommendation algorithms have become an effective approach to mine user behavior data and provide personalized product suggestions. Based on a public e-commerce user behavior dataset, this study uses the R language to conduct data cleaning, visualization, conversion funnel analysis, and logistic regression. Results show that user click browsing behavior occupies an absolute dominant proportion in all interactive behaviors, which accounts for 94%, while collection behavior is nearly absent, and add-to-cart behavior only accounts for a small proportion of total behaviors. The conversion funnel indicates serious user loss from click to collection, and the logistic regression shows that click, collection and add-to-cart behaviors have no significant driving effect on purchase conversion under the limitation of existing sample data without purchase records. This paper provides targeted suggestions for e-commerce platforms to optimize recommendation strategies and improve user conversion efficiency.

Keywords: Artificial Intelligence Recommendation Algorithm, E-commerce, User Behavior Data, Purchase Conversion, Logistic Regression

1. Introduction

In the current era of booming digital economy and big data application, the overall transaction scale of e-commerce continues to expand steadily, and major mainstream e-commerce platforms continuously enrich commodity categories, brand types and inventory quantity to meet diversified market demand [1]. Rich commodity resources bring users more abundant shopping choices, but also cause prominent information overload and commodity screening difficulties, which not only reduce users' shopping satisfaction and decision-making efficiency, but also restrict the improvement of platform transaction volume and user stickiness [2]. To alleviate this dilemma, e-commerce platforms widely apply artificial intelligence recommendation algorithms to deeply analyze user historical browsing and interactive behavior data, mine users' potential consumption preferences and shopping tendencies, and push targeted personalized commodity content for different user groups [3].

User behavior data generated on the platform mainly includes click browsing, commodity collection, add-to-cart and order placing, which constitutes the core data basis for the daily operation and iterative optimization of recommendation algorithms [4]. Different types of user behaviors

DOI: 10.54254/2755-2721/2026.CH34650

represent different levels of purchase intention: shallow click behavior reflects users' initial interest in commodities, while collection and add-to-cart belong to deep interactive behaviors, which are closer to users' real consumption demand and purchase willingness. Existing relevant academic research mostly focuses on the structural optimization of recommendation algorithm models and simple single-index analysis based on click-through rate, while lacking in-depth discussion on users' complete behavior path evolution and the differential influence of different interactive behaviors on purchase conversion effect [5].

Based on the above research background and existing research gaps, this paper takes real e-commerce user behavior data as the research carrier, uses R language to complete data preprocessing and visual modeling, and combines descriptive statistics, conversion path funnel analysis and logistic regression empirical test to systematically analyze the real distribution characteristics of platform user behavior under AI recommendation push. This research aims to reveal the internal logical correlation between user behavior characteristics and AI recommendation application effect, identify the key loss bottleneck in the user conversion path, and provide a reliable theoretical basis and practical operation reference for e-commerce platforms to adjust recommendation logic, allocate recommendation traffic reasonably and comprehensively improve user purchase conversion rate [6].

2. Theoretical foundation

2.1. Basic concept of recommendation system

A recommendation system is an important intelligent information filtering technology developed against the background of big data, which integrates artificial intelligence, data mining, mathematical statistics and multidimensional analysis methods [7]. It can automatically capture user preference characteristics and consumption habits by analyzing users' long-term browsing, consumption, and interactive behavior data and match highly relevant commodities and service content for users from massive platform information resources. As the core application carrier of artificial intelligence technology in the e-commerce industry, the recommendation system effectively solves the problem of information asymmetry between platforms and users, greatly reduces users' independent information search costs, and meanwhile, helps platforms increase commodity exposure rates, activate user activity and maintain long-term user stickiness [8].

2.2. Role of user behavior data in AI recommendation algorithms

User behavior data is the most original and core data source for training, updating and iterating e-commerce AI recommendation algorithms [9]. All interactive operation behaviors generated by users on the platform completely record the whole process of users' demand perception, interest screening and consumption decision-making. The algorithm builds user portrait labels and evaluates consumption ability and shopping tendency by quantifying the frequency, times and types of different user behaviors. Shallow click browsing behavior helps the algorithm quickly capture users' preliminary interest scope and preference direction, while deep collection and add-to-cart behaviors can accurately reflect users' real purchase intention and potential demand preference, which is the key judgment basis for the algorithm to realize accurate secondary recommendation and interested user recall [10].

DOI: 10.54254/2755-2721/2026.CH34650

3. Methodology

3.1. Research design

This research adopts an empirical analysis method based on cross-sectional e-commerce user behavior data. Firstly, the R language is used to complete original data sorting, duplicate value cleaning, missing value inspection and abnormal sample filtering to ensure data validity. Secondly, descriptive statistics and visual chart drawing are used to analyze the overall structure and distribution characteristics of different user behaviors. Thirdly, a conversion funnel model is constructed to measure the conversion rate and the user loss degree of each node in the standard consumption path. Finally, a binary logistic regression model is built to empirically test the specific influence of click, collection and add-to-cart behaviors on user purchase conversion. The whole research follows the rigorous logical path of data preprocessing, visual statistical analysis, conversion path mining and regression empirical test.

3.2. Data collection

The research data is selected from a classic open e-commerce user behavior dataset. The core data fields include unique user ID, commodity ID and user behavior type, covering four mainstream behavior categories: click browsing, commodity collection, add-to-cart and order placing. The overall research sample contains 836 valid user samples, with completely continuous daily behavior observation records, which can truly and objectively reflect the real interactive state and behavior preference of platform users under the push of the AI recommendation algorithm.

3.3. Data processing

This study takes the R language as the main analysis tool to complete all data preprocessing work, including duplicate value elimination, missing value detection, abnormal behavior sample filtering and invalid data deletion. All user IDs and commodity IDs are coded uniformly for subsequent statistical matching; four types of user behaviors are classified, summarized and counted to calculate daily behavior volume change trend and individual user total behavior frequency, which lays a solid data foundation for subsequent visual chart drawing and regression model empirical analysis.

3.4. Research methods

3.4.1. Descriptive statistical and visual analysis

The R language is used to draw user behavior time series trend charts, user behavior proportion pie chart and user individual behavior frequency distribution charts, to intuitively display the quantity structure, proportion distribution and crowd activity characteristics of click, collection and add-to-cart behaviors.

3.4.2. Conversion funnel analysis

Taking the classic standard consumption path of "click → collection → add-to-cart → purchase" as the research framework, this paper calculates the conversion rate and user loss rate of each link node, and identifies the main bottleneck link restricting the improvement of the platform transaction conversion rate.

DOI: 10.54254/2755-2721/2026.CH34650

3.4.3. Logistic regression analysis

Taking whether the user generates final purchase behavior as the dependent variable and taking click, collection, and add-to-cart behavior as independent variables, a binary logistic regression model is constructed to test the statistical significance and specific influence degree of each behavioral variable on purchase conversion decisions.

4. Results and discussion

4.1. Overall characteristic analysis of user behavior

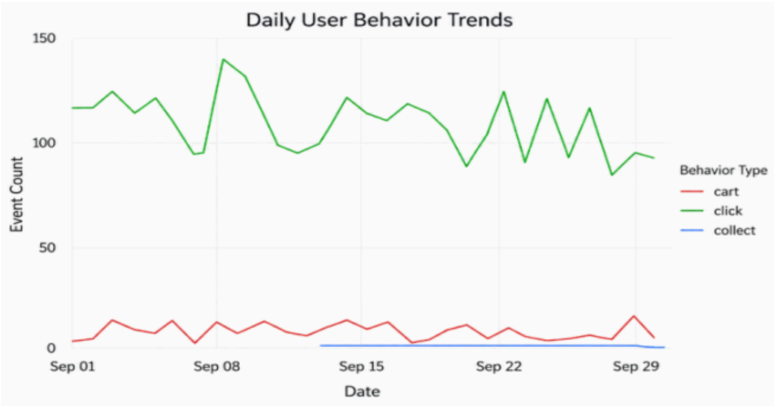

Figure 1. Daily trend of e-commerce user behavior

From the time trend of user behavior shown in Figure 1, click browsing behavior is always in an absolute dominant position throughout the whole observation cycle, and its daily activity quantity is far higher than add-to-cart and collection behavior. Add-to-cart behavior maintains a low-stable level all the time, while collection behavior almost does not generate effective records in the whole cycle. It reflects that most users only stay in simple browsing and shallow interest browsing after receiving AI-recommended commodities, and lack sufficient willingness to further collect and follow favorite goods.

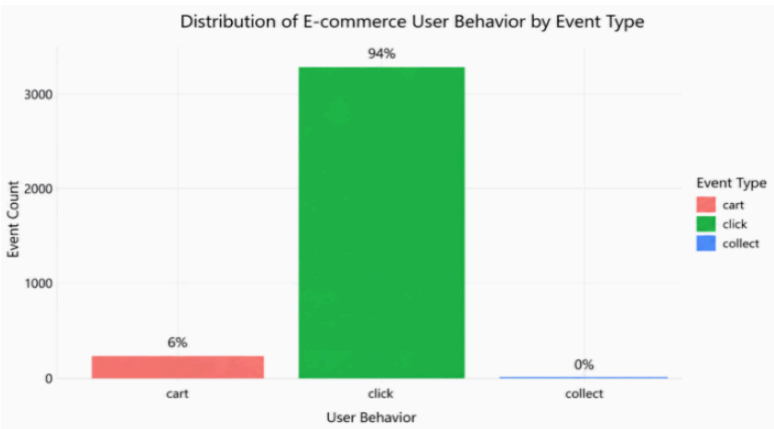

Figure 2. Proportion distribution of user behavior types

It can be clearly seen from Figure 2 that click behavior accounts for 94% of all user behaviors, add-to-cart behavior accounts for 6%, and collection behavior accounts for a proportion close to

DOI: 10.54254/2755-2721/2026.CH34650

zero. The overall user behavior structure presents an extremely unbalanced state, which indicates that the current AI recommendation algorithm has a strong ability to attract users to click and browse, but cannot effectively stimulate users' deep interactive willingness, such as collection and favorite attention.

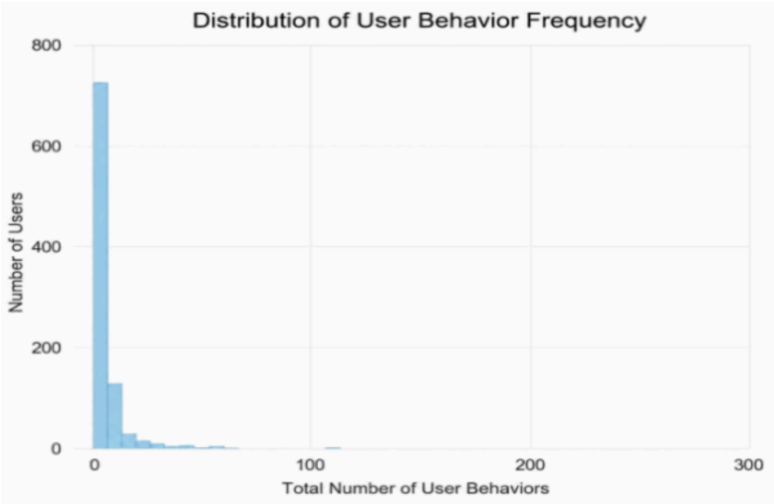

Figure 3. Frequency distribution of user individual behavior

Figure 3 shows that most platform users have low individual behavior frequency, which is mainly concentrated in the low interval of 0-10 times. Only a small number of users belong to high-frequency active groups with more than 100 behaviors. The overall user activity of the platform is obviously low, and most users belong to occasional passive browsing triggered by recommendation push, lacking actively independent shopping demand and interactive motivation.

4.2. User behavior conversion path analysis

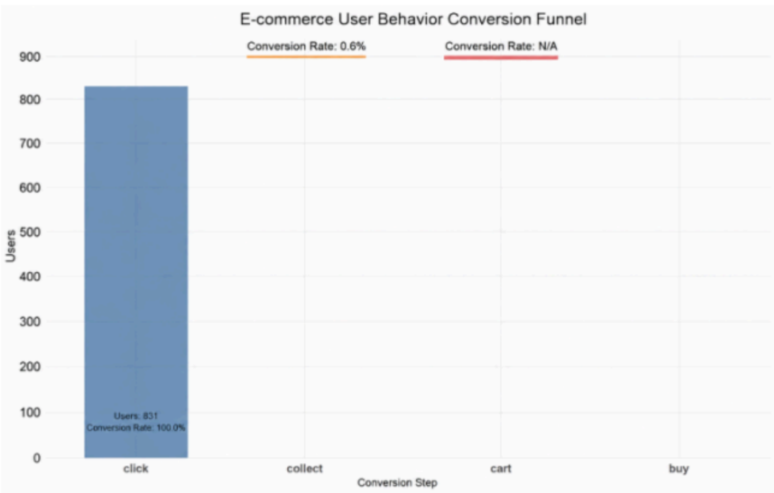

Figure 4. Conversion funnel of user behavior path

As shown in Figure 4, taking all click users as the starting base of the conversion path, the conversion rate from click to collection is only 0.6%, and there is no effective subsequent conversion to add-to-cart and purchase links. The most serious user loss occurs in the conversion

DOI: 10.54254/2755-2721/2026.CH34650

link from shallow click browsing to deep collection attention, which has become the core bottleneck restricting the improvement of platform's overall purchase conversion rate. It also fully reflects that the matching degree of AI-recommended commodities with users' real psychological expectations and potential demand is insufficient.

4.3. Logistic regression analysis results

	Variable	Estimate	Std. Error	P Value	Significance
	<chr>	<dbl>	<dbl>	<dbl>	<chr>
1	(Intercept)	0	115809.	1	ns
2	has_click	1	115659.	1	ns
3	has_collect	1	183866.	1	ns
4	has_cart	1	25756.	1	ns

Figure 5. Logistic regression results of user behavior on purchase conversion

According to the regression output results in Figure 5, the odds ratios of the click, collection and add-to-cart variables are all 1, and all p-values are greater than 0.05, showing no statistical significance. The core reason is that there is no effective purchase behavior sample record in the dataset, resulting in the model being unable to accurately identify the significant influence of each behavior factor on user purchase decision-making. It also indicates that single-dimensional user behavior data is difficult to support in-depth analysis of conversion-driving factors.

4.4. User activity heterogeneity analysis

Combined with user behavior frequency grouping, low active users occupy the absolute majority of the research sample. Limited by the absence of effective purchase records in the overall sample, there is no obvious difference in purchase conversion performance among user groups with different activity levels. Highly active users only increase daily browsing times and interactive frequency, but cannot form effective transaction transformation under the current AI recommendation mechanism.

5. Conclusion

This study analyzes e-commerce user behavior data using R language, visualization, conversion funnel analysis, and logistic regression. Three key conclusions are obtained. First, user behavior distribution is extremely unbalanced: click behavior accounts for 94% of all interactions, while collection behavior is nearly missing, indicating that most users only conduct shallow browsing. Second, the conversion path has a serious bottleneck; the conversion rate from click to collection is only 0.6%, leading to huge user loss and blocked transaction conversion. Third, because no valid purchase records exist in the dataset, click, collection, and add-to-cart behaviors show no significant predictive effect on purchase conversion in the regression model.

To improve recommendation effectiveness and conversion performance, e-commerce platforms should reduce excessive dependence on click indicators, strengthen the guidance from click to collection and add-to-cart, and carry out hierarchical user operations to activate low-active users.

This research is limited by data dimensions and the lack of complete purchase samples. In future studies, more comprehensive data with purchase records, product attributes, and user evaluations

DOI: 10.54254/2755-2721/2026.CH34650

can be used, combined with more advanced machine learning models, to further explore the driving mechanism of user conversion and optimize AI recommendation algorithms.

References

[1] Liu, Y. (2021). Research on the application of artificial intelligence recommendation algorithm in e-commerce. Journal of Electronic Commerce Research, 24: 36-45.
[2] Zhang, H., Wang, L. (2022). Empirical analysis of user behavior conversion based on e-commerce big data. Statistical and Decision Making, 38: 112-117.
[3] Li, J. (2020). Optimization strategy of e-commerce personalized recommendation system from user behavior perspective. Business Economics Review, 15: 78-83.
[4] Wang, Q. (2019). Development status and trend analysis of china's e-commerce industry under digital economy. Contemporary Economic Management, 41: 22-28.
[5] Chen, S. (2021). Information overload and user decision-making behavior in online shopping. Consumer Economics, 37: 55-61.
[6] Zhao, K. (2022). Principle and application progress of AI recommendation algorithm in e-commerce platform. Computer Engineering and Applications, 58: 41-49.
[7] Zhou, M. (2020). Value mining of user behavior data in e-commerce precision marketing. Marketing Weekly, 29: 66-70.
[8] Wu, T., Chen, Y. (2021). Research defects and improvement direction of current e-commerce recommendation algorithm. Journal of Intelligence, 40: 134-140.
[9] Huang, B. (2022). The impact of big data user behavior on e-commerce recommendation conversion. Modern Business, 18: 33-36.
[10] Van der Geer, J., Hanraads, J.A.J., Lupton, R.A. (2010) The art of writing a scientific article. J. Sci. Commun., 163: 51–59.