

AI Recommendation Algorithms and E-commerce Purchasing Behavior: A Value Chain Perspective

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Abstract: With the rapid development of artificial intelligence technologies, recommendation algorithms have become a crucial tool for e-commerce platforms to enhance user experience and improve conversion rates. Based on value chain theory, this paper systematically examines the influence mechanisms of AI recommendation algorithms on consumer purchasing behavior in e-commerce, focusing on key stages such as user acquisition, information matching, decision support, and post-purchase feedback. By reviewing relevant literature and constructing a theoretical model, the study explores the functional pathways of recommendation algorithms across different stages of the value chain and their combined effects on consumer cognition, emotions, and behavioral decisions. The findings indicate that recommendation algorithms significantly promote purchase intention and actual purchasing behavior by improving information matching efficiency, enhancing user experience, and reducing decision-making costs. Meanwhile, trust mechanisms and perceived value play mediating roles in this process. This study provides both theoretical support and practical insights for e-commerce platforms to optimize recommendation strategies and improve user conversion rates.

Keywords: AI recommendation algorithms; e-commerce; value chain; consumer purchasing behavior; influence mechanism

1. Introduction

In recent years, with the rapid development of internet and mobile communication technologies, e-commerce has profoundly transformed traditional business models. E-commerce enterprises represented by platforms such as Taobao, JD.com, Pinduoduo, and Amazon have significantly improved the efficiency of product circulation by continuously optimizing technological methods and operational models. However, as the variety of products continues to expand, the problem of information overload has become increasingly serious [1]. Users often find it difficult to quickly identify products that meet their needs, thereby affecting their shopping experience and the efficiency of their purchase decision-making.

Against this background, AI recommendation algorithms have gradually become an important tool for e-commerce platforms to enhance their competitiveness [2]. By analyzing users' browsing records, click behavior, purchase history, and review data, recommendation systems are able to accurately identify user preferences and deliver personalized product suggestions. This "personalized recommendation for different users" model not only significantly reduces users' information search costs, but also, to a certain extent, reshapes consumers' decision-making paths.

From the perspective of practical development, recommendation algorithms have been deeply embedded in various business processes of e-commerce platforms. For example, when users enter the homepage of a platform, the system provides personalized displays based on their historical behavior; during the product browsing process, the system recommends related products in real time; and after payment is completed, similar products are pushed to users in order to encourage repeat purchases [3]. This recommendation mechanism, which runs through the entire shopping process, indicates that artificial intelligence technology influences not only a single stage, but also reconstructs the entire e-commerce value chain.

However, although recommendation algorithms have been widely applied in practice, there is still a lack of systematic theoretical analysis of their impact on consumer purchasing behavior. In particular, exploring the mechanisms of recommendation algorithms at different stages from the perspective of the

value chain would contribute to a more comprehensive understanding of their pathways of influence[4]. Therefore, based on value chain theory, this paper divides e-commerce activities into four stages—user acquisition, information matching, purchase decision-making, and post-purchase feedback—to analyze the specific role of AI recommendation algorithms at each stage and to construct a model of their influence mechanisms.

2. Theoretical Foundation and Research Framework

2.1. The Operational Logic of E-commerce from a Value Chain Perspective

Value chain theory was originally developed to analyze how firms create and add value through a series of activities. In the context of e-commerce, the connotation of the value chain has been further expanded [5]. It not only includes traditional activities such as production, sales, and services, but also encompasses information acquisition, data processing, user interaction, and platform operation.

Compared with traditional business models, the core characteristics of e-commerce lie in being “data-driven” and “user-centered.” By continuously collecting user behavioral data, platforms transform it into valuable informational resources and utilize it across different stages to accurately capture user needs[6]. Therefore, the e-commerce value chain is essentially a dynamic process centered on information flow and oriented toward user experience.

From an overall process perspective, the e-commerce value chain can be understood as a continuous sequence consisting of “user acquisition – demand understanding – transaction facilitation – relationship maintenance.” [7]. These stages are not isolated; rather, they are closely interconnected through data and information, forming a closed-loop structure. In this process, AI recommendation algorithms serve as a key technological tool that runs throughout and continuously optimizes the efficiency of each stage.

2.2. Fundamental Principles and Application Characteristics of AI Recommendation Algorithms

AI recommendation algorithms are a technological approach that analyzes users’ historical behaviors, preference patterns, and contextual information to predict potential needs and deliver personalized content [8]. Their core lies in discovering patterns from data, enabling systems to “understand users” and provide information that better matches their needs.

In practical applications, recommendation algorithms typically rely on data such as users’ browsing records, click behavior, and purchase history. Through continuous accumulation and updating of data, the system gradually improves the accuracy and relevance of its recommendations. This capability of continuous learning endows recommendation systems with strong adaptability and dynamic optimization characteristics[9].

In addition, recommendation algorithms exhibit notable real-time responsiveness and interactivity[10]. On the one hand, systems can generate instant recommendations based on users’ current behavior; on the other hand, each user action feeds back into the system and influences subsequent recommendations, thereby forming a continuous feedback loop. This bidirectional interaction makes recommendation systems not merely tools for information delivery, but also important factors influencing user behavior.

2.3. Logical Construction of the Research Framework

Based on the value chain perspective, this study systematically examines the role of AI recommendation algorithms in e-commerce from an overall process standpoint. Unlike approaches that focus primarily on variable relationships, this paper emphasizes analyzing the specific functions of recommendation algorithms at different stages and their impacts on user behavior within real operational processes.

Specifically, before users enter the platform, recommendation algorithms attract potential users through targeted exposure; during the browsing process, algorithms enhance information matching efficiency through personalized recommendations [11]; when users make selections and comparisons, recommended content influences their judgments and decisions; after the transaction is completed, the system maintains user relationships and promotes repeat purchases through continuous recommendations.

Through this logical structure, it becomes clearer how recommendation algorithms operate

throughout the entire e-commerce value chain and play differentiated roles at different stages. Meanwhile, this process-based analytical approach helps avoid the limitations of a single perspective and enables a more comprehensive understanding of the impact of recommendation algorithms on consumer purchasing behavior.

3. The Mechanisms of AI Recommendation Algorithms within the Value Chain

3.1. Mechanisms in the User Acquisition Stage

At the initial stage of the e-commerce value chain, user acquisition serves as the foundation for value creation^[12]. Traditional e-commerce models mainly rely on search engine optimization, advertising, and price promotions to attract users; however, these approaches often suffer from insufficient precision and low conversion efficiency. The introduction of AI recommendation algorithms has shifted user acquisition strategies from “broad coverage” to “precise targeting.”

By analyzing user behavioral data—such as browsing history, click preferences, dwell time, and social interactions—recommendation algorithms can construct relatively detailed user profiles. Based on these profiles, platforms are able to deliver product information precisely to potential users. For instance, on short-video or content-based platforms, systems analyze users’ viewing preferences and present product information in a “content-oriented” manner, allowing users to encounter products naturally during entertainment, thereby reducing the intrusive nature of advertisements.

Moreover, recommendation algorithms can leverage a “similar user expansion” mechanism, applying the behavioral characteristics of existing users to potential user groups to achieve targeted traffic acquisition. This approach not only improves the efficiency of user acquisition but also enhances the quality of new users, making them more likely to convert into actual consumers.

From a value chain perspective, the role of recommendation algorithms in the user acquisition stage lies not only in increasing user volume, but more importantly in improving the degree of match between users and the platform, thereby laying a solid foundation for subsequent value creation.

3.2. Mechanisms in the Information Matching Stage

After users enter the platform, information matching becomes a key factor influencing user experience. In the e-commerce environment, the vast number of products can impose high information processing costs on users if effective filtering mechanisms are lacking, thereby reducing purchase intention.

AI recommendation algorithms continuously learn from users’ historical behavior to dynamically identify their interests. On this basis, systems can prioritize the display of the most relevant products. For example, in homepage recommendations, “You May Also Like” sections, and personalized lists, algorithms rank products according to user preferences, enabling users to quickly locate desired items.

This precise matching not only improves the efficiency of information acquisition but also enhances users’ psychological identification with the platform. When users repeatedly receive recommendations that align with their needs, they gradually develop trust and dependence, perceiving that the platform “understands them.” Such experiential improvements are difficult to achieve through traditional search-based models.

Furthermore, recommendation algorithms introduce a certain degree of diversity to avoid overly homogeneous recommendations. While recommending relevant products, systems also incorporate different types of items with potential relevance, thereby expanding users’ choice sets. This balance between “relevance and diversity” contributes to an overall improvement in user experience.

Therefore, at the information matching stage, recommendation algorithms effectively reduce information asymmetry, enhance user satisfaction, and provide important support for subsequent purchasing behavior by optimizing the presentation of information.

3.3. Mechanisms in the Purchase Decision Stage

The purchase decision stage is one of the most critical components of the e-commerce value chain. At this stage, users must compare and select among multiple alternatives, and recommendation algorithms play an important guiding role in this process.

By integrating multidimensional information, recommendation algorithms assist users in making decisions. For example, systems display product sales volume, user reviews, ratings, and “others also bought” information. These elements partially substitute for the experiential aspects of offline shopping and reduce user uncertainty.

Recommendation algorithms also influence users’ allocation of attention through information ranking. Studies have shown that users are more likely to click on top-ranked products; therefore, the ranking process indirectly affects user decision-making. This influence is often subtle and does not significantly interfere with users’ autonomy, yet it effectively improves conversion rates.

Additionally, recommendation systems promote higher-value consumption through “bundled recommendations” and “associated recommendations.” For instance, when users browse a particular product, the system recommends complementary or upgraded items, encouraging additional purchases. This approach not only increases platform revenue but also satisfies users’ diverse needs to some extent.

From a psychological perspective, when users continuously receive positive signals (such as high ratings and strong sales performance) during the decision-making process, their perceived risk decreases and their confidence in purchasing increases, making them more likely to complete transactions. Therefore, in the purchase decision stage, recommendation algorithms not only provide informational support but also facilitate purchasing behavior by influencing users’ cognition and judgment.

4. Existing Problems

4.1. Information Homogeneity and the Lack of Diversity in Recommendation Content

In the practical application of AI recommendation algorithms, platforms typically rely on users’ historical browsing records, click behavior, and purchase data to deliver personalized recommendations. Although this “interest reinforcement” logic can improve recommendation accuracy in the short term, it also tends to lead to information homogeneity. As algorithms continuously reinforce users’ existing preferences, the types of products exposed to users become increasingly fixed, resulting in a lack of novelty and variation in recommendation content, which in turn limits users’ choice space.

In the e-commerce context, this phenomenon is reflected in users being repeatedly exposed to products of the same category or style over a long period, making it difficult for them to discover new products of potential interest. While this approach helps improve click-through rates and conversion rates, in the long run it may reduce users’ sense of novelty and willingness to explore, weaken platform attractiveness, and negatively affect user retention. Therefore, how to achieve a balance between recommendation accuracy and content diversity has become a critical issue that recommendation systems urgently need to address.

4.2. Lack of Transparency in Recommendation Mechanisms and Insufficient User Trust

Most recommendation algorithms currently used by e-commerce platforms operate as typical “black-box” systems, making it difficult for users to clearly understand how recommendations are generated. When recommended content deviates from users’ actual needs, users are often unable to identify the reasons, which may lead to doubts or even distrust toward the recommendation system.

For example, after browsing a certain type of product, users may continue to receive similar recommendations without understanding how their behavior has been recorded and used by the algorithm. This lack of explainability places users in a passive position, potentially raising concerns about algorithmic “manipulation.” Particularly when recommendations exhibit clear commercial intent, users are more likely to develop resistance. Therefore, while improving efficiency, recommendation systems may also undermine users’ trust in the platform to some extent, which is unfavorable for long-term development.

4.3. Data Privacy and Information Security Risks

The operation of AI recommendation algorithms relies heavily on the collection and analysis of large volumes of user data, including browsing behavior, purchase history, preference patterns, and even certain sensitive information. While this data-driven approach enhances recommendation effectiveness, it also introduces significant privacy and security risks.

On the one hand, inadequate regulation in data collection and usage may infringe upon users' privacy rights; on the other hand, data breaches or misuse can cause direct losses to users and severely damage the platform's reputation. Moreover, as users' awareness of privacy protection continues to increase, excessive data collection and highly personalized recommendations may lead to discomfort and resistance, thereby reducing trust in the platform. Therefore, achieving a proper balance between data utilization and privacy protection is a crucial issue that e-commerce platforms must carefully address.

4.4. The Impact of Over-Commercialized Recommendations on User Experience

In practice, some e-commerce platforms, in pursuit of higher conversion rates and profitability, may incorporate strong commercial orientation into their recommendation mechanisms. For example, they may prioritize high-margin or promoted products rather than those that best match users' needs.

Although such profit-driven recommendation strategies may yield short-term economic benefits, they can negatively affect user experience in the long run. When users frequently receive recommendations that do not fully align with their actual needs, they may develop fatigue or even aversion, leading to reduced platform usage. Additionally, overly frequent recommendation pushes may disrupt users' normal browsing experience, causing recommendation systems to shift from being "assistive tools" to "sources of interference," thereby weakening overall platform attractiveness.

4.5. Algorithmic Bias and Uneven Product Exposure

During the operation of recommendation algorithms, optimization based on historical data and click-through rates often leads to a "rich-get-richer" effect, where popular products receive more exposure, while less popular but high-quality products struggle to be discovered.

This phenomenon not only affects the diversity of the platform's product ecosystem but also places small and medium-sized merchants at a disadvantage in competition. From the user's perspective, overly concentrated recommendation results reduce the richness of choices and limit access to potentially valuable products. Therefore, how to balance recommendation efficiency with fairness is a key issue that must be considered in the optimization of recommendation systems.

4.6. Increasing User Dependence on Algorithmic Recommendations

As recommendation algorithms continue to improve, users have become increasingly dependent on system-generated recommendations during the shopping process. While this dependence enhances efficiency to some extent, it may also weaken users' ability to make independent choices.

When users become accustomed to relying on recommended content for decision-making, their active search and comparison behaviors may decline, potentially causing them to miss products that better meet their needs. Moreover, excessive reliance on algorithms may lead to more passive decision-making and reduce rational consumption. In the long run, such behavioral changes may have a profound impact on users' consumption habits. Therefore, while improving convenience, maintaining users' autonomy in decision-making is also an important issue that platforms need to address.

5. Countermeasures and Recommendations

5.1. Optimizing Recommendation Mechanisms to Enhance Content Diversity

To address the problems of information homogeneity and the "filter bubble," e-commerce platforms should introduce mechanisms that enhance content diversity while maintaining recommendation accuracy. During the recommendation process, platforms should not rely solely on users' historical behavior for one-dimensional content delivery; instead, they should also take into account users' potential interests and exploratory needs by appropriately incorporating products of different types or styles, thereby broadening users' choice space.

For example, a certain proportion of "exploratory recommendations" may be incorporated into the recommendation system, allowing users to encounter new product categories while still maintaining interest relevance. This approach not only helps enhance users' sense of novelty and overall experience, but also strengthens platform attractiveness and user loyalty, thereby contributing to long-term value creation.

5.2. Improving Recommendation Transparency to Strengthen User Trust

To address the lack of transparency in recommendation mechanisms, platforms should improve the explainability of algorithms to help users develop a basic understanding of recommendation logic. For example, simple explanations such as “recommended based on your browsing history” or “similar users are also interested in this” may be provided to clarify the source of recommendations.

At the same time, platforms may offer functions that allow users to adjust their recommendation preferences, enabling them to actively participate in the recommendation process rather than passively receiving content. This approach not only enhances users’ sense of control, but also helps improve their trust in the platform, thereby alleviating concerns about algorithmic “manipulation” to some extent.

5.3. Strengthening Data Management to Ensure User Privacy and Security

To address data privacy and security risks, e-commerce platforms should establish more comprehensive data management mechanisms and strictly comply with relevant regulations in the collection, storage, and use of data. On the one hand, the scope of data usage should be clearly defined to avoid excessive collection and misuse of user information; on the other hand, technical protection measures should be strengthened to reduce the risk of data leakage.

In addition, platforms should inform users of how their data are used through clear privacy policies and notification mechanisms, thereby enhancing users’ sense of security and trust. Achieving a proper balance between data-driven operations and privacy protection is an important prerequisite for the sustainable development of recommendation systems.

5.4. Balancing Commercial Objectives and User Experience

To address the problem of over-commercialized recommendations, platforms should strike a balance between economic returns and user experience when optimizing recommendation strategies. Recommendation systems should not be guided solely by profit maximization, but should pay greater attention to users’ actual needs and experiences.

In practice, this can be achieved by improving the recommendation ranking logic so that users are more likely to encounter products that genuinely match their interests, rather than merely those that are being promoted. At the same time, the frequency of recommendation pushes should be appropriately controlled to avoid excessive disruption to the user experience. Only when user experience is properly safeguarded can platforms achieve stable and sustainable long-term development.

5.5. Optimizing Algorithm Structure to Improve Recommendation Fairness

To address algorithmic bias and uneven product exposure, platforms should introduce more reasonable allocation strategies into recommendation mechanisms to ensure that different types of products have opportunities for display. For example, recommendation weights can be adjusted so that some high-quality but less-exposed products receive a certain amount of visibility, thereby enriching the platform’s product ecosystem.

Meanwhile, recommendation processes should avoid excessive reliance on single indicators such as click-through rates, and instead take into comprehensive consideration multiple factors, including product quality and user feedback. By optimizing the algorithmic structure, platforms can improve recommendation efficiency while also taking fairness and diversity into account, thereby promoting the healthy development of the platform ecosystem.

5.6. Guiding Rational Consumption and Reducing Excessive Dependence

To address the growing dependence of users on recommendation systems, platforms should improve convenience while also encouraging users to maintain a certain degree of autonomy in their choices. For example, by optimizing search functions and category navigation, platforms can encourage users to actively explore product information on their own.

At the same time, recommendation content may include comparative information and diversified options to support more rational decision-making. In addition, platforms can use prompts or guidance mechanisms to remind users to make choices based on their actual needs, thereby avoiding excessive

dependence on algorithmic decision-making. Through such measures, platforms can improve efficiency while preserving the rationality and independence of users' consumption behavior.

6. Conclusions

From the perspective of the value chain, this paper systematically analyzes the mechanisms through which AI recommendation algorithms function in e-commerce. By examining stages such as user acquisition, information matching, purchase decision-making, and post-purchase feedback, it can be seen that recommendation algorithms are no longer limited to being a single technical tool; rather, they have become a crucial supporting force throughout the entire e-commerce process. At different stages, recommendation algorithms exert continuous and profound influence on consumer purchasing behavior by precisely reaching users, optimizing information distribution, assisting decision-making, and promoting sustained consumption.

Overall, AI recommendation algorithms have significantly improved the operational efficiency of e-commerce. On the one hand, they effectively reduce users' information search costs, enabling users to find products that meet their needs more quickly. On the other hand, they enhance user experience through personalized recommendations, thereby increasing conversion rates and user loyalty. At the same time, recommendation algorithms have also, to some extent, reshaped traditional consumption patterns, making users' purchasing paths increasingly dependent on data and algorithmic support.

While fully demonstrating their positive effects, recommendation algorithms have also introduced a series of new problems, including information homogeneity, insufficient user trust, data privacy risks, and over-commercialization. These issues affect user experience and the long-term development of platforms to varying degrees, indicating that recommendation systems still require continuous optimization and adjustment in practical application. Therefore, while using recommendation algorithms to improve efficiency, e-commerce platforms should place greater emphasis on user experience and data security, and promote the development of recommendation mechanisms in a more reasonable, transparent, and sustainable direction.

In general, AI recommendation algorithms have become one of the key factors driving the development of e-commerce and are playing an increasingly important role in every stage of the value chain. In the future, with continuous technological advancement, recommendation systems will further develop toward greater diversity, personalization, and human-centered design while improving accuracy. In this process, how to achieve a balance between efficiency and fairness, as well as between personalization and privacy protection, will remain an important issue in the field of e-commerce.

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