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The Differences in the Commercialization Paths of the Recommendation Algorithms of Douyin and Taobao

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Abstract. Recommendation algorithms have become a key driving force for the commercialization of platforms in the contemporary digital economy, profoundly influencing user experience and revenue generation methods. E-commerce platforms reshape consumption patterns by relying on massive user data and commodity resources. This article uses a comparative analysis method to examine the different commercialization paths of recommendation algorithms on content platform Douyin and e-commerce platform Taobao. Research shows that the Douyin algorithm takes models such as graph neural networks (GNN) as its core. Its primary optimization goal is to increase user dwell time and interaction rate to accumulate traffic value. Subsequently, it achieves commercialization through native advertising and the "content seeding combined with live-streaming sales" model. Taobao's algorithm is based on collaborative filtering and transformer architecture, directly and precisely optimizing the transaction conversion rate (GMV) by "goods finding people". Its commercialization mainly relies on advertising monetization and transaction commissions. This article delves deeply into the causes of the differences, attributing them to the fundamental differences in the essence of the platform ecosystem, the logic of user behavior, the iterative paths of algorithms, and the priorities of business goals. This research can deeply analyze the coupling relationship between technical design and business strategy, providing decision-making references for platform operators and algorithm designers.

Keywords: Recommendation algorithm commercialization path, Douyin, Taobao, platform ecosystem.

1. Introduction

Recent years, with the vigorous development of the digital economy and the rapid progress of artificial intelligence technology, e-commerce platforms have gradually evolved from early middlemen undertaking transaction functions between users to comprehensive digital ecosystem platforms integrating traffic distribution, price formation and user experience optimization [1]. The massive amount of product information has led to a rise in users' decision-making costs. Traditional search and classification mechanisms are difficult to meet personalized demands, and an AI-driven e-commerce recommendation system has emerged to meet these requirements [2]. The richness of big data in e-commerce stems from the diverse behaviors of users on the platform. Every time users browse products, search for keywords, complete a purchase or leave a review, a large amount of data

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is generated, which provides valuable information resources for e-commerce platforms [3]. According to the 54th "Statistical Report on the Development of China's Internet" released by the China Internet Society (CNNIC), by June 2024, the user base of online videos (including short videos) in China will reach 1.068 billion, and the user base of online shopping will reach 908 million. The overall number of users is quite large. This makes personalized recommendation a key intermediary connecting users with content and products [4]. The recommendation algorithm not only determines what users will see, but also deeply influences the platform's traffic allocation logic and revenue model. The recommendation algorithm is the core asset of the platform, and its design logic fully reflects the platform's business model and value orientation [5]. The "2024 China Mobile Internet Semi-annual Report" shows that the average monthly usage time of Douyin users has exceeded 35 hours. The play volume of its e-commerce content increased by 47% compared with the same period last year. Taobao is a leading enterprise among traditional e-commerce platforms, with its recommended traffic accounting for over 40%, making it the second largest traffic entry point after searching [6]. Against this backdrop, Douyin and Taobao are representative platforms in the content and e-commerce fields, and their commercialization paths for recommendation algorithms are quite different: Douyin uses content to stimulate interest and achieve the conversion of "goods finding people" through seeding. The core of Taobao is to match demands and optimize the transaction of "people looking for goods". Understand the difference between these two paths.

Existing research explores the integration of recommendation algorithms and platform commercialization from three aspects. The first category focuses on algorithm technology and optimization. Early research sorted out the limitations of collaborative filtering algorithms. After the rise of deep learning, related architectures have shown potential for large-scale application [7]. Domestic scholars have also systematically reviewed the application value of graph neural networks in recommendation systems, laying the foundation for understanding the algorithmic capabilities of the platform [8]. The second category explores the connection between algorithms and business models. Some studies have analyzed the impact of algorithm design on merchant exposure and consumer choice, while others have pointed out that algorithm design should take into account both user experience and business interests. The research by Cheng Ke and Zhao Pan confirmed the effectiveness of Douyin's "content seeding" logic, providing empirical support for this paper [9]. The third category conducts a comparative analysis of Douyin and Taobao. However, existing research either fails to deeply compare the algorithmic logics of the two or only focuses on operational strategies rather than algorithmic mechanisms or does not specifically discuss the commercialization paths of the algorithms. Overall, there is a lack of systematic comparison and in-depth cause analysis of the commercialization paths of the recommendation algorithms of the two [10]. This paper aims to study the commercialization path of Douyin and Taobao.

2. The commercialization path of Douyin's recommendation algorithm

2.1. The algorithm model is adapted to the monetization goal

The success of Douyin's recommendation algorithm can be naturally attributed to its thorough understanding of the characteristics of the content ecosystem and excellent technical adaptation. That is, its core algorithm models, the GNN and the interest diffusion model, are not designed for direct commodity transactions, but are clearly aimed at the best match between content and users' potential interests. Therefore, this system has an extremely detailed and acute capture of users' real-time behavior signals: explicit likes, comments, and shares, as well as implicit behaviors such as dwell time, completion rate, repeated playback, and quick swiping away, are all collected in a timely manner. What is even more remarkable is the use of stream computing technology to process behavioral data within seconds, updating user interest vectors in real time and accurately, making the recommendation results precisely match the current focus of users' attention, thereby increasing users' dwell time and interaction rate. This is precisely the traffic foundation for Douyin's advertising monetization and e-commerce monetization This enables the recommendation results to truly align with the user's current focus of attention and psychological state.

Due to the characteristics of the selected technical path, the primary monetization goal of the Douyin algorithm can be clearly and reasonably defined: it is not the direct GMV, but the user's dwell time and interaction rate. The platform consciously and systematically recommends content that users may be interested in, thereby prolonging the time users spend within the APP and creating an immersive browsing experience. High duration and high interaction are not only the foundation of the platform's traffic value but also naturally create the best scenarios for the embedding of commercial information. Therefore, the commercialization of Douyin is essentially a typical "indirect approach" strategy: the algorithm first ensures the superiority of the content consumption experience, thereby naturally accumulating users' interest tags and trust relationships, and then conducting advertising reach and e-commerce conversion based on this. The research conducted by Cheng Ke and Zhao Panpan on the duration of e-commerce short videos has well confirmed this point: in the Douyin ecosystem, the appeal of the content itself (influencing duration) is the most definite and important prerequisite for commercial conversion [11].

2.2. Core commercialization model

Since the commercialization model discussed is based on the previous algorithmic logic, Douyin has naturally developed two core commercialization pillars: advertising monetization and e-commerce monetization. The advertising monetization system is uniformly and completely supported by the "ByteDance Engine". From brand exposure to effective conversion, there is a clear and natural process connection. Its basic mechanism is the ECPM (Expected Revenue per Thousand Impressions) bidding. Therefore, the advertiser's bid, together with the system's estimation of click-through rate and conversion rate, determines the display sequence of the advertisement. What is even more remarkable is that Douyin's algorithm achieves the originality of advertisements through the style matching of AD content with natural content and the dynamic regulation of AD loading rates. For instance, the form of information flow advertisements is consistent with that of short videos, and the platform keeps the AD loading rate between 10% and 15%, which not only ensures advertising revenue but also avoids a decline in user experience. Information flow advertising, search advertising and splash screen advertising are all different forms of products in this system. E-commerce monetization is a crucial step for Douyin to truly transform its traffic advantage into transaction strength. Therefore, its model can be naturally summarized as "content seeding + live-streaming sales." The algorithm first recommends content in the form of daily short videos, allowing merchants or influencers (Kols) to plant "interest-based" content about the products, thereby establishing a preliminary understanding and forming a good impression in the minds of users. When a user has a clear interest in a certain type of product or a certain creator (i.e., follows and interacts frequently), the algorithm will promptly and fully recommend relevant live-streaming content to them. The live streaming room itself is a consumption scene where real-time interaction, detailed explanations, and time-limited promotions are highly integrated. Therefore, it can directly stimulate the impulse to purchase and effectively shorten the decision-making path from "interest" to "purchase". What is even more remarkable is that this approach breaks the traditional e-commerce search logic of "people looking for goods" and opens up a new paradigm of "goods finding people".

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2.3. Traffic distribution and commercial conversion links

Douyin has a very clear and mature traffic distribution mechanism for its traffic distribution and commercial conversion chain, which is based on the basic framework of "traffic pool" and "inverted triangle progressive distribution". Douyin divides its traffic pool into 9 levels. New content initially enters the basic traffic pool with 500 to 1000 views. If the completion rate is ≥30%, it can enter the next level of the traffic pool. Then, based on the core interaction data (completion rate, like rate, and comment rate) obtained in this volume pool, it is determined whether to recommend it to a larger traffic pool. Therefore, it can be said that Douyin's traffic distribution itself is a content racecourse. A racecourse refers to a hierarchical competition mechanism for traffic based on content interaction data. High-quality content can receive more traffic recommendations through data assessment. High-quality or promising content and products (such as product promotion videos and live-streaming rooms) can thus quickly break through and naturally achieve viral spread

A typical business conversion chain is very natural and reflects the characteristics of content driven. Content exposure is used to stimulate interest, thereby promoting various behaviors such as clicking, jumping, and closing deals. Specifically, there are short videos or live-streaming content first, which are precisely exposed by algorithms. The content itself serves the function of "stimulating interest". Therefore, if users are moved by the content, they will take actions such as clicking on the shopping cart, the yellow cart, or entering the live-streaming room. At this point, the algorithm then timely and effectively uses the built-in e-commerce tools to complete the jump and conversion guidance. Li Hongshan's research on Douyin's rural bloggers has provided an extremely clear and insightful empirical analysis: The blogger attracts the attention of urban users (traffic) with the content about the rural landscape and the process of growing agricultural products. Then, the process of picking and packaging on the spot during the live stream naturally and fully stimulates the purchasing desire and promotes sales (sales volume). Therefore, a complete and efficient closed loop has been formed from public domain traffic to private domain fans and then to e-commerce transactions.

3. The commercialization path of Taobao's recommendation algorithm

The above analysis has covered the commercialization path of Douyin's recommendation algorithm, whose core features are determined by the essence of the content ecosystem. As a representative of traditional e-commerce platforms, the commercialization path of Taobao's recommendation algorithm is significantly different from that of Douyin. The following text will analyze Taobao's commercialization path from the same dimension and lay a phenomenological foundation for the subsequent analysis of the causes of the differences.

3.1. The algorithm model is adapted to the monetization goal

Since the algorithm model and monetization goals are different from Douyin's "content finds people" logic, it can be naturally pointed out that: As a mature e-commerce platform, the fundamental purpose of Taobao's recommendation algorithm is to achieve the precision and efficiency of "goods finding people". Therefore, Taobao adopts a hybrid model of user-based collaborative filtering (UCF) and product-based collaborative filtering (ICF). UCF explores the shopping preferences of similar users, while ICF explores the correlation between products. And the latest Transformer architecture model (capturing the long-term dependencies of users' sequential behaviors) all center on precise matching of supply and demand. The Taobao algorithm is based on

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the explicit or potential shopping demand signals of users as the fundamental data foundation. Therefore, the algorithm makes reasonable processing of various signals in a hierarchical and weighted manner. The "Taobao History" section provides a very clear and rigorous explanation of this: The strongest signals are search keywords, historical purchase records, and additional purchase/collection behaviors, all of which directly reflect the purchase intention. Next come auxiliary signals such as recommendation stream clicks and live room stays. Then there are global scene signals constructed based on elements such as the user life cycle and consumption capacity. From this, the algorithm can naturally and accurately mine users' historical and real-time behavior data, ultimately forming a long-term user profile with extremely fine granularity and rich dimensions, including various features such as consumption preferences, price elasticity, and brand tendencies. Therefore, the goal orientation of Taobao's recommendation algorithm is extremely direct and pure: to enhance the accuracy of product matching and the final transaction conversion rate. For every optimization of the recommended position and every adjustment of the ranking, the ultimate assessment indicator is whether it brings about a higher click-purchase conversion rate, a higher average transaction value or a better repurchase rate. All iterations of the algorithm serve to reduce the decision-making cost for users, presenting the most likely transaction item at the moment when users "want to buy".

3.2. Core commercialization model

As the commercialization model of Taobao is highly consistent with the positioning of the Taobao platform, its main and typical commercialization model can naturally be summarized as advertising monetization and transaction commission. Advertising monetization essentially serves the needs of merchants to obtain traffic. Therefore, advertising products such as "Direct Train" (search keyword bidding advertising) and "Diamond Display" (display advertising) are naturally and fully integrated into the platform's "search + recommendation" traffic system. Its charging model (such as pay-per-click CPC, pay-per-display CPM, etc.) itself is a typical effect-oriented design. More importantly, whether an advertisement is displayed and where it is displayed are objectively and intelligently determined by the platform's algorithm based on various factors such as the estimated click-through rate, conversion rate, and merchant bids. Therefore, the platform can perfectly balance the maximization of advertising revenue and the optimization of traffic allocation efficiency. Transaction commissions are the most stable and largest source of income for platforms apart from advertising revenue. Therefore, Taobao/Tmall platforms charge merchants a certain percentage of technical service fees (commissions) based on the transaction volume (GMV) of different product categories. This naturally ties the platform's interests to the merchants' sales performance and also prompts the platforms to proactively optimize their algorithms and improve their ecosystems. Strive to promote the growth of transaction volume.

3.3. Traffic distribution and commercial conversion links

The logic of Taobao's traffic distribution and commercial conversion chain is very clear, mature and complete. It can be naturally summarized as "recall - ranking - fine ranking": First, a batch of product candidate sets that may meet the user's needs are "recalled" from the product pool. Then, several rounds of "ranking" models are used to conduct detailed scoring and ranking on this candidate set based on over a hundred factors such as click-through rate, conversion rate, unit price, and merchant service rating. Finally, the results are displayed to the users. What is even more remarkable is that search traffic and recommendation traffic work in harmony and complement each

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other within the Taobao system: search serves as the entry point for users to actively put forward clear demands, while recommendation is a means to meet users' vague demands and explore potential ones. The data of the two are interconnected, enhancing the accuracy of user profiling for each other.

The conversion path of Taobao users has a very obvious and predictable purpose. When the demand is clear, search/recommend, compare and select, place an order and close the deal. When users enter Taobao, they mostly have a clear shopping intention (even if this intention is still vague), so active search or browsing the recommendation flow can naturally lead to this purpose. Therefore, Taobao's algorithm provides the most appropriate product recommendations in the user's "comparison and selection" stage, promoting efficient decision-making. More importantly, the entire conversion chain is based on stable user demands and relies on the long-term accumulation of product data on Taobao. Its fundamental goal is to enhance conversion efficiency at every stage of the user's shopping process and ultimately achieve a transaction.

4. In-depth analysis of the causes of differences

Through the above analysis, the core phenomenon differences in the commercialization paths of Douyin's and Taobao's recommendation algorithms have been clearly identified. These differences are not accidental but are jointly determined by multiple factors such as the underlying ecosystem, behavior, technology, and strategy of platforms. The following text will deeply analyze the reasons for the formation of these differences from four dimensions and clarify the hierarchical relationship of each factor.

4.1. The essential differences in platform ecosystems

The essential differences in platform ecosystems. The fundamental reason for the divergence in commercialization paths between Douyin and Taobao lies in the underlying logic of the content ecosystem and the e-commerce ecosystem, that is, the essential differences in their platform ecosystems: Douyin originated from the content ecosystem, so its underlying assets are a large amount of non-standardized content in the form of short videos. The core relationship can be naturally summarized as "user - content - creator". The prosperity of an ecosystem is inevitably premised on abundant content, active creation, and user immersion. Therefore, the algorithmic logic of Douyin should naturally serve the efficient distribution of content and the optimization of the consumption experience. Taobao was established as the foundation of an e-commerce ecosystem, so its underlying assets are standardized goods and services. The basic relationship is "user - product - merchant". The prosperity of the ecosystem inevitably requires efficient matching of supply and demand, trustworthy transactions, and guaranteed fulfillment. Therefore, Taobao's algorithm has always been committed to improving transaction efficiency as its fundamental mission. For this reason, the different ecological genes of Taobao are essentially like different operating systems and naturally determine the design philosophy and operation rules of the upper-level algorithm.

4.2. The user behavior logic is different

Due to the different behavioral logics of users, the demand characteristics of entertainment consumption and shopping decisions have very clear and distinguishable differences: the main behavioral logics of users on different platforms are different, so the response methods of algorithms are also different. Specifically speaking, users on the Douyin platform are in a state of entertainment

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consumption. Their behaviors are obviously random, impulsive and emotionally driven. Generally, users do not have a clear purpose and are just killing time. They are also very likely to immediately shift their interest because of a certain viral video. Therefore, the Douyin algorithm must pay close attention to real-time interest capture and achieve rapid response. When users are browsing the recommendation stream on Taobao, their minds are basically in the state of making shopping decisions or preparing to purchase. Therefore, their behaviors have clear purposefulness, comparability and rationality. Behaviors such as searching, adding to purchase and comparing prices are all stronger and more reliable demand signals. Therefore, Taobao's algorithm places greater emphasis on the accumulation and mining of users' historical behavior data, and also more proactively and systematically predicts users' stable preferences and demands at each stage of their life cycle.

4.3. Algorithm iteration path adaptation

Due to the distinct ecological and behavioral logics of real-time interest capture and historical demand accumulation, there is a very clear and natural distinction in the iterative paths of their algorithm technologies. The algorithmic technology orientation of Douyin is real-time, short-term, and multi-interest parallel: Therefore, Douyin uses stream processing technology to handle the behavioral data updated in seconds, employs a multi-interest modeling network to simultaneously and fully extract the various possible interest clusters of users at present, and uses reinforcement learning to actively and promptly discover new interests of users. Thus, it effectively solves the problem of information cocoons and ensures the freshness and appeal of the content. The technical direction of Taobao's algorithm is very clear, namely in-depth, long-term and scenario-based prediction. Therefore, Taobao first systematically and solidly builds long-term user profiles, then uses a fine tag system and reasonable attenuation model to naturally distinguish short-term impulses from long-term preferences and deeply integrates the two major functions of search and recommendation. More importantly, it is necessary to make precise demand predictions based on scene factors such as geographical location and user life cycle (for example, giving priority to recommending household items when users are in the decoration stage). This naturally leads to the satisfaction of cross-cycle demands.

4.4. Algorithm iteration path adaptation

The strategic choice between short-term traffic monetization and long-term transaction value.

The strategic choice between short-term traffic monetization and long-term transaction value is essentially a concrete manifestation of the different business strategic priorities of the platform. As the most prominent and reliable advantage of Douyin as a latecomer is to capture users' attention, its commercialization must logically prioritize the maximization of short-term traffic value, that is, to directly and fully convert the traffic advantage into financial benefits through high-density advertising loading and aggressive e-commerce expansion. As a mature trading market, the healthy development of Taobao's ecosystem inevitably requires a balance among merchant profits, consumer satisfaction, and platform growth. Therefore, Taobao places more emphasis on the cultivation and maintenance of long-term transaction value, and thus naturally pays attention to various long-term indicators such as repurchase rate, customer lifetime value (LTV), and merchant retention rate. In line with this, its commercialization methods (differentiated commissions, membership systems) also focus on encouraging user behaviors and business operations that are conducive to long-term value creation.

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5. Conclusion

This study adopts a comparative case study method, taking Douyin and Taobao as the objects, to sort out the core differences in the commercialization paths of their recommendation algorithms, and analyzes the causes of the differences from four aspects: platform ecological attributes, user behavior patterns, algorithm evolution directions, and emphasis on commercial goals. The research finds that the differences between the two are reflected in three aspects: in terms of algorithm models and monetization goals, Douyin accumulates traffic by focusing on user stay and interaction through GNN and interest diffusion models, while Taobao directly pursues transaction conversion rates by relying on collaborative filtering and the Transformer architecture. In terms of commercialization models, Douyin monetizes through "content seeding + live-streaming sales" and native advertising, while Taobao makes profits by using advertisements such as Express Train and commissions from transactions. In terms of traffic distribution and conversion, Douyin uses a hierarchical traffic pool to regulate exposure, while Taobao matches products with user demands through a funnel logic of "recall - ranking - precise ranking". The underlying reason lies in the fact that Douyin is a content ecosystem. Facing users who consume entertainment and have random behaviors, its algorithm focuses on real-time interest capture and prioritizes short-term traffic monetization. Taobao is an e-commerce ecosystem that serves users with clear shopping intentions. Its algorithm focuses on long-term demand prediction, emphasizing long-term transaction value and ecological balance. This study integrates algorithm research into the platform ecosystem and business model framework, revealing the coupling relationship between algorithms and business strategies, providing references for the operation of content and e-commerce platforms. Subsequently, the impact of algorithm transparency, privacy protection, and cross-platform algorithm integration on commercialization can be explored."

References

[1] Qian, R. (2025) Application of artificial intelligence in e-commerce recommendation system and its efficiency optimization. E-Commerce Letters, 14, 2150.
[2] Zhang, H. and Zhou, L. (2025) Generation mechanism and governance path of AI recommendation algorithm discrimination in e-commerce platform. E-Commerce Letters, 14, 5754.
[3] Liu, Y. (2025) Research on Ethical Risk and Legal Regulation of Intelligent Recommendation Algorithm in Social E-commerce Platform. E-Commerce Letters, 14, 166.
[4] China Internet Network Information Center (2024) The 54th statistical report on China's internet development.
[5] Cheng, K. and Zhao, P. (2025) Research on the prediction of multimodal fusion model for the optimal duration of e-commerce short videos — Based on the data of Tik Tok platform. E-Commerce Letters, 14, 1980.
[6] Liu, Y. (2025) Study on the mode of e-commerce live broadcast and consumers' purchase intention in Tik Tok. Frontier in Economics and Management, 1.
[7] Li, C., Qi, Z., Wang, Y. and Song, X. (2025) Research on User Growth Strategy of Social E-commerce Platform Based on AARRR Model — Taking Tik Tok Platform as an Example. E-Commerce Letters, 14, 3161.
[8] Li, H. (2025) From traffic to sales — User transformation path and e-commerce marketing strategy optimization of Tik Tok three rural bloggers. E-Commerce Letters, 14, 1047.
[9] Zhou, S. (2025) Research on the influence of personalized recommendation page design of Taobao on consumers' purchase decision. E-Commerce Letters, 14, 2750.
[10] Ge, Q. (2025) Comparative Study on Marketing Strategies of Social E-commerce Platforms — Taking Tik Tok, Aauto Quicker and Xiaohongshu as Examples. E-Commerce Letters, 14, 8.
[11] Zhang, S. and Du, C. (2025) From "Flow Field" to "Business Ecological Domain": Research on the Evolution Path of Platform Function of Tik Tok APP. Journal and Communications, 13, 1769.