A Review of the Guiding Mechanism of Social Media Recommendation Algorithms on User Consumption Behavior

Rongfei Liu

Media & Prof Communications, University of Pittsburgh, Pittsburgh, USA
olivialiu040319@163.com

Abstract. With the rapid development of social media, recommendation algorithms play an increasingly important role in information dissemination and user consumption. However, existing studies have examined technical mechanisms or short-term behavior, neglecting the impact of algorithms on consumption culture and long-term social outcomes. Therefore, this study explores the mechanisms via which social media recommendation algorithms guide user consumption behavior and shape consumption culture, while exploring user, platform, and algorithm interactions. Through literature review and case study methods, it analyzes relevant academic studies and practical examples from typical social media platforms to reveal how algorithms influence consumption decisions and behaviors via mechanisms of content distribution, psychological inducement, and dynamic co-construction. The results indicate that recommendation algorithms alter users' information access and consumption choices while shaping the consumption culture through trends, social identity, and instant gratification. Besides, platforms use commercial logic to reshape distribution and enhance user experience via perception-feedback, boosting traffic and commercial value.

Keywords: Social Media, Recommendation Algorithm, Consumption Behavior, Guiding Mechanism, Collaborative Construction

1. Introduction

In the digital age, social media has deeply integrated into daily life, and recommendation algorithms examine user activity and item characteristics to offer personalized recommendations, continuously affecting how users encounter information and consume. Existing studies have enhanced knowledge of social media recommendation algorithms and user consumption behavior, especially in terms of technological integration and attention-guidance logic. For instance, the adaptation of collaborative filtering and deep learning algorithms and their impact on reallocating user attention have been explored. Nevertheless, the consumption guidance under the "algorithm-platform-user" framework remains underexplored, and the mechanisms by which algorithms shape consumption culture have not been studied in depth. To fill an existing gap, this study investigates the guiding role of social media recommendation algorithms in user consumption. Through the use of literature review and case study approaches, this study investigates the practical paths of algorithm-guided consumption. In particular, it explores the development of platform recommendation mechanisms in response to technological and business changes, the role of recommendation algorithms on user consumption, the joint influence of users, platforms, and algorithms on the consumption ecosystem, and the long-term effects and risks of algorithm-driven consumption. Thus, the clarification provides guidance for algorithm governance, user behavior, platform strategies, and the social media ecosystem.

2. The evolution logic of the platform recommendation mechanism

2.1. The evolution of recommendation mechanisms and platform embedding

The recommendation mechanisms on social media platforms have evolved alongside technological advancements, with platforms increasingly leveraging algorithms to direct user attention and shape content consumption. In the early stages, recommendations largely followed simple rules, such as ranking popular content. With the rapid growth of users and data, collaborative filtering algorithms were gradually adopted to recommend content based on user similarity [1]. For example, Facebook utilized users' friend relationships and interaction data to recommend groups or product pages that users might follow. Furthermore, the development of deep learning enabled Neural Collaborative Filtering (NCF) to optimize recommendation accuracy by mapping the user-item interaction matrix to a low-dimensional space to learn features [2]. In order to fulfill users' psychological needs and drive engagement, platforms started favoring content with emotional or extreme characteristics. For instance, Instagram uses image recognition and deep learning to analyze the styles of images that users like and collect, recommending similar brand advertisements. This integrates recommendation technology with visual social scenarios, shifting product recommendations from text-based to immersive formats. In addition, federated learning technology has been used to enable collaborative model training across devices or platforms without compromising user privacy [3]. As technology advances, platforms now reshape information visibility, affecting attention and content consumption.

2.2. The distribution logic of attention-driven content algorithms

By leveraging recommendation algorithms, social media platforms have built an institutionalized attention economy, in which user attention serves as a core resource for allocation and management, ultimately maximizing traffic conversion and commercial value. Besides, platforms use algorithms to capture attention, shape user behavior, and convert it from attention to traffic and consumption. Specifically, algorithms rank content based on user behavior, such as dwell time and engagement. This process exceeds mere technical modeling and reflects a dissemination framework in which platforms transform attention into usable data and assign it to content via recommendation systems. For example, TikTok uses reinforcement learning to quickly test how different types of short videos attract user attention, pinning content with high completion and engagement rates to the top, thus forming institutionalized rules for attention allocation [4]. In contrast, YouTube prioritizes clickbait or controversial content, monetizing user attention [5]. Besides, platforms shape user expectations and interactions via segmentation and content tagging. They use trending topics to attract attention and utilize likes, comments, and other interactions to steer focus, distribute attention across content, and enhance user engagement. This mechanism boosts dwell time and channels attention into traffic and conversions. Moreover, cross-platform collaboration further strengthens the institutional effects of the attention economy. For instance, by sharing data, social media and e-commerce platforms can prioritize product recommendations, which prolongs attention and drives cross-platform conversion from attention to consumption [6].

2.3. The strategic guidance of content via recommendation systems

Through recommendation algorithms, social media platforms build communication systems that determine “whose voice is heard” and “which issues receive attention,” while also commercializing public issues and directing user attention toward traffic and commercial value.

In particular, algorithms establish content agenda rights. Through the closed-loop process of data, model, and feedback, technical rules are converted into content allocation authority. Consequently, platforms embed core objectives like user dwell time, interaction rates, and business conversion into algorithms, making agenda selection strongly biased toward platform goals. For example, short-video platforms tend to recommend emotionally stimulating and low-cognitive-cost content, while high-cognitive-cost content, such as in-depth analysis or public policy discussions, is marginalized, leading to a public agenda skewed toward entertainment and fragmentation [7]. Besides, algorithms reinforce “filter bubbles” via user profiling, shaping a consumption-oriented public discourse while shaping users’ existing preferences and constraining consensus. In environmental issues, algorithms may direct extreme or skeptical content to different user groups, intensifying polarization. Platforms consequently channel attention in particular directions, thus establishing control over the discourse. For example, they reduce environmental protection to green consumption, which weakens scrutiny of structural issues. Features such as likes, comments, rewards, and paid promotions further embed discourse within commercial logic, creating a structure dominated by paying entities. Platforms use content ranking and recommendation systems, together with ecosystem tools such as WeChat Mini Programs, to link browsing with purchasing, creating a content-to-consumption cycle. Furthermore, cross-platform and community-based recommendations further guide attention and consumption [7].

3. The mechanism of recommendation algorithms in shaping consumption behavior

3.1. The attention redistribution mechanism in content distribution

Recommendation algorithms guide user attention, reshaping information reception and distribution. In this process, platforms establish user profiles from multiple data sources and apply text mining, behavior analysis, and deep learning to convert comments, product details, browsing, and purchase history into interest tags, highlighting top content. This mechanism forms an “interest-feedback-re-recommendation” loop, shifting information dissemination from decentralized to centralized and influencing consumption behavior. The prioritized recommendation of content changes the path via which users access information, shifting them from active searching to algorithmic feeding. In turn, users passively receive content through interactions like infinite scrolling and refreshing, without explicitly expressing their needs. At the same time, timing-based interventions help guide attention and shape the flow of information. For example, during the “Double Eleven” shopping festival, platforms conduct A/B testing several weeks in advance to set the recommendation weights for tags like “limited-time discounts” and “scenario-based cases,” and embed pre-sale countdowns and best-seller lists into the feed, directing users’ attention to key promotional periods and thereby enhancing purchase behavior. By placing consumption-related content at the forefront of information feeds, recommendation algorithms disrupt the conventional balance of information distribution. For instance, Twitter prioritizes brand tweets and shopping links for users with a propensity to consume, steering attention from social interaction to product information [8]. Similarly, Pinterest highlights high-potential products based on users' browsing history and attention mechanisms, focusing users' attention on specific items during immersive browsing and shifting consumption decisions from broad exploration to precise selection [9]. By adjusting recommendation weights at different times, algorithms concentrate user attention at key moments, forming an "attention-content-consumption" loop and converting the effect of information distribution into actual consumption behavior.

3.2. The psychological induction mechanism in personalized recommendations

By targeting users' psychological responses, recommendation algorithms guide consumer behavior during participation and trigger purchase intentions at cognitive and emotional levels, thus making consumption shaped by both content and psychological factors. In particular, platforms leverage social proof by showcasing "others' purchases or usage," eliciting users' conformity and reinforcing self-identity. For example, Instagram includes tags such as "over 100,000 users have purchased" in its recommendations, encouraging users to follow the behavior of the crowd [10]. At the same time, personalized recommendations cater to users' self-identity needs by generating identity labels and a sense of group belonging, making it easier to deliver content that resonates psychologically. For instance, algorithms recommend specialized fitness equipment to exercise enthusiasts, reinforcing their identity labels and encouraging consumption. Besides, algorithms use interactive participation mechanisms. By tracking and analyzing specific user interactions including likes, comments, and shares, algorithms establish a "behavior-recommendation-behavior" cycle that boosts targeting and accuracy through predictive feedback loops. For instance, on Douyin, interactive recommendation ads use this mechanism so that users who like or comment are subsequently presented with similar products, creating an "interaction-recommendation-consumption" loop that translates engagement into purchases. By simulating social interactions, algorithms enhance users' sense of self-worth and identity, while recommending products that match user interests lowers resistance to consumption, effectively turning engagement behaviors into triggers for repeated purchases [11]. For instance, on Taobao, sharing shopping experiences are linked with extra product recommendations, encouraging repeat purchases. In addition, algorithms exploit scarcity psychology to further induce consumption. By tagging products as "low stock" or "limited edition," platforms trigger users' fear of missing out, accelerating purchases and influencing both behavior and psychology.

3.3. The generation logic of consumer culture shaped by algorithms

By influencing user behavior, recommendation algorithms help shape the formation of consumption culture, which emerges via content distribution, algorithmic reinforcement, and user internalization. In particular, platforms promote the emergence and popularity of specific consumption cultures by increasing the distribution frequency of selected content and amplifying trending topics through algorithmic mechanisms. For instance, content frequently recommended on Xiaohongshu, such as camping lifestyle and minimalist skincare, has come to symbolize emerging consumption cultures [12]. And these lifestyles spread rapidly among users through continuous exposure and algorithmic amplification, resulting in observable trends and fashions. At the same time, algorithms shape users' consumption values by emphasizing instant gratification and personalized experiences. Short-video and live-streaming e-commerce platforms encourage immediate satisfaction or impulse purchases through recommendations of fast-moving consumer goods or customized products. Features such as "watch-and-buy" consumption, limited-time offers, and exclusive items trigger a "fear of missing out," undermining rational judgment and promoting impulse buying. Through these mechanisms, algorithms reproduce consumption culture continuously, embedding specific behavioral norms into users' daily practices. In addition, users further internalize recommended content into their lifestyles and social expression via participation, sharing, and interaction. Activities like liking, commenting, and posting reinforce users' engagement with algorithm-driven content and align them with new consumption trends. Thus, a self-reinforcing cycle develops, where consumption patterns, lifestyles, and social practices interconnect. In this process, algorithms influence users' perceptions of the "ideal life" and turn personal consumption into collective behavior.

4. The collaborative construction relationship of users platforms - algorithms

4.1. Dynamic co-construction mechanism of user behavior and recommended content

There exists a two-way interaction between user behavior and recommended content. Specifically, user behavior provides fundamental data for algorithmic recommendations and also plays an active role within the algorithmic dissemination structure, reflecting the essence of "co-construction." As a result, this mechanism can expand users' consumption boundaries, with user interests and platform recommendations reinforcing each other, thus forming a continuous behavior-recommendation-new behavior cycle. If users display interest in fashion content, the algorithm delivers more relevant brand information, reinforcing browsing patterns and maintaining a continuous interaction loop [13]. For example, if a Douban user marks an art film as "want to watch," the algorithm may recommend similar films and related cultural and creative products, transforming the user from a mere film enthusiast into a consumer within the cultural and creative domain. Moreover, social relationships shape the co-construction of user behavior and recommended content. By collecting user behavior data and analyzing preferences, platforms can push content that matches users' interests, facilitating content migration and shifts in user interests. In this process, social ties serve as a medium within the dissemination process, enabling the algorithm to make effective use of user behavior data. Users' interactive behaviors on social platforms, such as sharing with friends or liking products, are also included in recommendations. For example, WeChat Channels considers individual and friends' behavior to highlight social influence and spread consumption across networks.

4.2. The mechanism of communication structure reshaping driven by business logic

In pursuit of commercial goals, platforms rely on algorithms to reorganize the dissemination system, forming a triangle linking algorithm, structure, and consumer power. In the pursuit of advertising monetization and commercial revenue, algorithms adjust information flows and resource allocation to favor high-consumption users and branded content, thereby concentrating traffic and enhancing marketing value [14]. For example, WeChat Official Account recommendation algorithms prioritize traffic to verified brand accounts, hence making their content more easily visible to users. Similarly, TikTok's branded live-streaming rooms leverage algorithms to reach the top of the traffic pool, where users passively receive brand information, boosting the brand's impact on consumer choices. The restructured dissemination system shifts users' purchasing power, giving brands an edge via algorithmic promotion while limiting users' options and strengthening brand influence [15]. At the same time, this structural reshaping gives rise to a new role of "algorithmic intermediary," making algorithmic operations more industrialized and structurally refined. Multi-channel network agencies apply algorithmic rules to help brands optimize content distribution, thus serving as intermediaries between brands and platform algorithms. Platforms like Facebook and Instagram set up professional teams to boost ad reach and brand awareness through algorithmic support [16]. This mechanism boots dissemination and shapes consumption, creating more complex flows under commercial logic.

4.3. Algorithm response strategy mechanism based on user perception

Platform algorithms adjust recommendation strategies by perceiving user feedback, transforming the recommendation mechanism from a purely technical tool into an emotional communication regulator, aimed at balancing user experience with commercial objectives. Algorithms can detect users' positive or negative perceptions and optimize recommended content and display strategies accordingly, forming a "perception-feedback-re-recommendation" loop. If users experience fatigue or negative emotions toward repetitive content, algorithms optimize the experience through content diversification and brand display adjustments. For example, algorithms track users' video scrolling frequency and viewing time to detect preferences and signs of fatigue, then adjust content variety or brand presentation. Conversely, when users actively engage with a brand's content, the algorithm raises that brand's recommendation weight and display priority, generating a positive feedback loop [17]. Moreover, with technological advances, algorithms can respond to user perceptions more precisely. Some platforms use affective computing to analyze comments and interaction emotions, refining recommendation relevance and push frequency [18]. For example, when a platform detects strong negative emotions toward a particular product recommendation, the algorithm reduces push frequency, analyzes the underlying cause, optimizes content matching, and boots the effectiveness and intelligence of the response strategy. This mechanism helps platforms improve experience and drive conversion via a perception-feedback loop guiding consumer behavior.

5. Conclusion

This study investigates the guiding mechanism of social media recommendation algorithms on user consumption behavior. The results show that algorithms, aligned with platform characteristics and business goals, form an attention-driven logic that shapes consumption through content distribution, decision-making, and value formation. Besides, user behavior, platform strategies, and algorithmic adjustments interact dynamically, collectively shaping the digital consumption ecosystem. However, the study relies on literature and case studies without quantitative data, focusing only on short-term effects and providing limited insight into long-term, intergenerational, or ethical impacts. Future research could utilize big data and experiments to measure algorithmic impacts, assess long-term effects, and explore improvements via technology, policy, and user education.

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