ISSN: 2472-3703 DOI: 10.6911/WSRJ.202611_12(11).0003

Managerial Effects and Consumer Response Mechanisms in Algorithmic Recommendation: A Review and Prospect

Chuchu Sun, Yihan Wang

Southwest Petroleum University, Chengdu, China

Abstract

With the rapid development of the digital economy, algorithmic recommendation has become a core hub connecting enterprises and consumers, profoundly reshaping the underlying logic and practical paradigms of marketing management. This paper systematically reviews the research trajectory of algorithmic recommendation in the management field, constructs an analytical framework of "technical features - management effects - consumer responses", dissects the technical attributes and management scenario adaptation logic of algorithmic recommendation, explores its management value in enhancing marketing efficiency, optimizing customer experience, strengthening brand relationships, and promoting product innovation, as well as the potential risks in algorithmic dependence, algorithmic discrimination, privacy leakage, and ethical disputes. Then, based on relevant theories, it deconstructs the cognitive assessment, emotional response, and behavioral decision-making mechanisms of consumers. Finally, it proposes future research directions such as algorithmic ethics governance and the integration effect of emerging technologies. This paper aims to integrate scattered research results and provide theoretical references and practical inspirations for enterprises to optimize algorithm management strategies and enhance consumer experience.

Keywords

Algorithmic recommendation; Consumer response; Managerial effect; Trust mechanism; Technological ethics.

1. INTRODUCTION

As we enter the era of the digital economy, algorithmic recommendationhas been elevated from an auxiliary tool to a core management element for enterprises, permeating every stage of the value chain, including product R&D, marketing communication, and customer relationship management. According to the China Internet Development Report (2023), the usage rate of algorithmic recommendation among China's internet platforms has reached 83.2%, with application penetration rates in fields such as e-commerce, content entertainment, and financial services all exceeding 75%. Through big data analytics and machine learning technologies, algorithmic recommendation achieves "one person, one face" personalized matching, thereby not only reducing enterprises' marketing costs and improving resource allocation efficiency, but also providing consumers with precise information screening and decision-making support [1].

In the field of marketing management, algorithmic recommendation has become an important strategic tool for enterprises to build competitive advantage. It uncovers consumers' potential demand to drive product innovation and service optimization and form differentiated competitive barriers; at the same time, through continuous tracking of user behavior and iterative feedback, it builds a dynamic customer relationship management system to enhance

ISSN: 2472-3703 DOI: 10.6911/WSRJ.202611_12(11).0003

consumer loyalty and lifetime value [2]. However, while algorithmic recommendation yields managerial benefits, it also gives rise to a series of managerial challenges. Problems such as market discrimination caused by algorithmic bias and "information cocoons" triggered by excessive personalization not only affect consumer experience but also place higher demands on enterprises' compliance management and ethical development [3].

Existing research has carried out discussions from perspectives such as technological optimization, consumer behavior, and ethical governance, but there is a lack of systematic integration of the managerial effects of algorithmic recommendation, and the mediating mechanisms and moderating conditions through which algorithmic characteristics affect consumer responses have not been deeply revealed [1]. On this basis, this paper first analyzes the technical attributes of algorithmic recommendation and its suitability for managerial scenarios, then conducts an in-depth analysis of the managerial value and potential risks of algorithmic recommendation and deconstructs the response mechanism of consumers to algorithmic recommendation, and finally proposes future research directions, thereby providing theoretical support for enterprises to optimize their algorithm management systems.

2. THE TECHNICAL ATTRIBUTES OF ALGORITHMIC RECOMMENDATION AND ITS ADAPTATION TO MANAGEMENT SCENARIOS

The managerial effects of algorithmic recommendation arise from the interaction between technological attributes and managerial scenarios; different technological characteristics exhibit differentiated application effects in different scenarios, and the logic of fit between the two constitutes the foundation of the research.

2.1. The Core Technical Characteristics of Algorithmic Recommendation

The technical attributes of algorithmic recommendation are the core thatgenerates management effects, and they mainly consist of four key dimensions.

2.1.1.Personalization Degree

As a core attribute, its technical logic is that personalized recommendation technology, through the algorithm's powerful data analysis, identification, and processing capabilities, builds user preference profiles based on the content consumers have preferred over a past period, and after grasping most of consumers' intentions, recommends specific content to specific consumers [4]. Highly personalized recommendation enables consumers to receive and consume the information they prefer at lower search costs, but excessive personalization can lead consumers to fall into "information cocoons" and enter a "homogeneous" environment, making the public's information horizon susceptible to being disciplined by algorithms [3].

2.1.2.Transparency

This refers to the degree to which consumers can understand the functions, logic, decision-making basis, and potential impacts of an algorithmic system. It does not require the disclosure of all source code, but rather emphasizes the explainability and accountability traceability of system behavior, decision-making processes, and attribution of responsibility, and it is a key factor affecting consumers' trust in algorithms [5]. The "black box effect" of algorithms makes it difficult to explain their operating processes and decision-making mechanisms to consumers, thereby triggering various concerns among consumers, whereas transparent algorithms reduce perceived risk and increase acceptance of recommendation results [6].

2.1.3.Interpretability

This refers to the understandability of algorithmic recommendation results, that is, whether consumers can understand the recommendation logic. Unlike transparency, which focuses on the disclosure of the algorithmic process, explainability pays more attention to explaining the

ISSN: 2472-3703 DOI: 10.6911/WSRJ.202611_12(11).0003

rationality of the results. E-commerce platforms help consumers understand the recommendation logic through information such as "based on your browsing history" and "users similar to you also like this." Research shows that algorithmic recommendations with good explainability reduce consumers' cognitive load and increase their willingness to accept the recommended content [5].

2.1.4.Fairness

This refers to the property whereby algorithmic recommendation is unbiased across different consumer groups and product types; it should not cause discrimination based on consumers' characteristics such as gender and age, nor should it excessively favor popular products while overlooking niche demand. Algorithmic fairness is directly related to the order of market competition and the protection of consumers' rights and interests. Unfair recommendations can harm the interests of vulnerable groups and trigger consumer resistance; therefore, fairness constraints should be embedded at the algorithmic design stage to balance personalized demand with the goal of social fairness [7].

2.2. The Core Management Scenarios for Algorithm Recommendation Adaptation

The core management scenarios of algorithm recommendation mainly consist of four categories. The requirements for algorithm technical attributes vary significantly in different scenarios.

2.2.1.Product Recommendation Scenario

In e-commerce scenarios, algorithmic recommendation is used for product recommendation and personalized search ranking, and its core objective is to increase conversion rates and average order value, so the level of personalization and precision is particularly important[8]. In content platform scenarios, algorithms are used for the precise push of content such as videos and articles, and a balance must be sought between personalization and diversity to prevent the "information cocoon" effect [9].

2.2.2.Marketing Communication Scenario

Algorithmic recommendation is used in precise advertising delivery and the customized production of marketing content, and its core objective is to improve marketing efficiency and reduce costs. Based on consumers' characteristics and behaviors, it can precisely predict demand and provide personalized advertising content, thereby increasing click-through rates and conversion rates. In such scenarios, algorithmic transparency and fairness are extremely important, because opaque algorithmic advertising can easily trigger consumer resistance, and discriminatory recommendations can spark consumer boycotts and damage brand reputation [10].

2.2.3.Customer Relationship Management Scenario

Algorithmic recommendation is used in customer segmentation, the provision of personalized services, and the detection of early warning signs of customer churn, and its core objective is to enhance customer trust and loyalty. By analyzing customers' past transaction data, it identifies the demand characteristics and value levels of different customer segments, provides customized services to high-value customers, and implements churn prevention measures for customers likely to churn. Algorithmic transparency and fairness are key to maintaining customer relationships: transparent algorithms strengthen customer trust, and fair algorithmic recommendations improve the customer experience [5].

2.2.4.Resource Allocation Scenario

Algorithmic recommendation is used in product R&D, inventory management, and channel optimization, and its core objective is to improve the efficiency of enterprises' resource utilization. By analyzing market demand data and changes in consumer preferences, it predicts

ISSN: 2472-3703 DOI: 10.6911/WSRJ.202611_12(11).0003

product demand trends, guides R&D and production planning, and optimizes inventory structure. The precision and timeliness of algorithms are particularly important, as highly accurate demand forecasting helps enterprises optimize resource allocation, increase their speed of response to the market, and strengthen competitiveness [2].

3. THE MANAGEMENT EFFECT OF ALGORITHMIC RECOMMENDATION: VALUE AND RISK

Algorithm recommendation, as an important tool for enterprise management, not only creates significant management value but also comes with potential risks. A comprehensive understanding of both aspects is the prerequisite for optimizing the algorithm management system.

3.1. The Core Management Value of Algorithmic Recommendation

Algorithm recommendation, through technological empowerment, demonstrates various management values and becomes an important support for enterprises to enhance their core competitiveness.

3.1.1.Improve Marketing Efficiency

Traditional marketing suffers from problems such as ambiguous targeting and homogeneous content. Algorithmic recommendation, by contrast, can achieve precise matching between marketing content and audiences through big data analytics and machine learning technologies [11]. Research shows that the efficiency of precision marketing based on algorithmic recommendation is more than 30% higher than that of traditional methods, while marketing costs are reduced by about 20%. Furthermore, it can dynamically optimize marketing strategies based on real-time feedback from consumers, thereby ensuring the sustainability of marketing effectiveness.

3.1.2.Optimize Customer Experience

In an era of information overload, consumers face difficulty in screening vast amounts of information. Algorithmic recommendation precisely identifies needs and provides personalized information and product recommendations, thereby reducing information search costs and the difficulty of decision-making. For example, Netflix's algorithmic recommendation system precisely delivers video content based on data such as users' viewing history and rating behavior, greatly improving users' viewing experience. High-quality algorithmic recommendation enhances consumers' perceived value and satisfaction, and further strengthens loyalty [12].

3.1.3.Strengthen Brand Relationships

Algorithmic recommendation strengthens the emotional connection between consumers and brands through continuous personalized interaction, thereby enhancing brand awareness. However, excessive recommendation can backfire, so enterprises should focus on fostering consumers' brand attachment, appropriately extend the brand value of products or services, attract consumers through experience enhancement, and build a well-rounded feedback mechanism [13].

3.1.4.Promote Product Innovation

Algorithmic recommendation, by analyzing consumers' behavioral data, preference characteristics, feedback information, and so on, precisely grasps market demand trends and potential demand, thereby providing data-based support for product development. E-commerce platforms leverage algorithms to analyze behavioral data such as consumers' browsing history and product purchase records, discover unmet needs, and support enterprises in developing new products and optimizing existing products [8].

ISSN: 2472-3703 DOI: 10.6911/WSRJ.202611_12(11).0003

3.2. The Potential Management Risks Associated with Algorithmic Recommendations

Algorithmic recommendation, while creating management value, also brings multiple potential risks, which enterprises need to pay close attention to and manage.

3.2.1.Algorithm Dependence

Problems arise, such as consumers becoming overly dependent on recommendation results and losing their capacity for autonomous decision-making, or enterprises relying too heavily on algorithmic data and thereby neglecting market changes and genuine needs. Research shows that on the consumer side, because attention and the accumulation of expertise are limited, excessive reliance on algorithms makes suboptimal decision-making more likely. On the enterprise side, over-reliance on algorithmic data can lead to a "data trap," causing enterprises to overlook sudden market fluctuations and consumers' latent needs, thereby affecting the quality of strategic decision-making [14].

3.2.2.Algorithmic Discrimination

The decision rules of algorithmic recommendation are based on learning from past data. If bias exists in past data, the algorithm will amplify that bias and produce discriminatory recommendation results. For example, search engine algorithms may, due to gender bias contained in past data, deliver more high-paying job opportunities to men and more low-paying job opportunities to women. Algorithmic bias not only harms the interests of socially disadvantaged groups and gives rise to social fairness problems, but also becomes a factor causing enterprises to face regulatory penalties and brand reputation crises [15].

3.2.3.Privacy Disclosure

Algorithmic recommendation requires the collection of large amounts of consumers' personal data. If an enterprise's data security management is inadequate, privacy leaks are likely to occur, harming consumers' rights and interests. Privacy leaks not only trigger a crisis of consumer trust and provoke resistance to algorithmic recommendation, but may also violate laws and regulations such as the Personal Information Protection Law, potentially exposing enterprises to legal liability [7].

3.2.4.Ethical Arguments

The "black box" effect of algorithmic recommendation can lead to problems such as algorithm abuse and the manipulation of consumer behavior. Some enterprises use algorithms to analyze consumers' psychological weaknesses and deliver inducement-oriented product recommendations to encourage impulse buying. At the same time, it brings about unfair market competition: dominant enterprises monopolize data and traffic through algorithms, squeezing the space for survival of small and medium-sized enterprises and undermining the order of market competition [16]. Therefore, controversies over algorithm ethics not only provoke public criticism but may also lead to stricter regulatory policies, affecting the normal operation of algorithmic recommendation by enterprises [6].

4. CONSUMERS' RESPONSE MECHANISM TO ALGORITHMIC RECOMMENDATIONS

Consumers are the direct targets of algorithmic recommendation, and their responses directly determine the managerial effectiveness of algorithmic recommendation. Consumer responses constitute a complex psychological and behavioral process influenced by multiple factors such as cognition, emotion, and context, and their core response mechanism can be analyzed from three aspects: cognitive evaluation, emotional response, and behavioral decision-making.

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4.1. Cognitive Assessment Mechanism

Cognitive evaluation is consumers' primary psychological response to algorithmic recommendation, referring to judgments about the appropriateness, credibility, and usefulness of recommendations. Its core influencing factors include the characteristics of the algorithm, the characteristics of consumers, and the characteristics of products.

4.1.1.Algorithm Characteristics

The characteristics of the algorithm include the aforementioned degree of personalization, transparency, explainability, and fairness. The degree of personalization affects the perceived usefulness of recommendations, and recommendations with a high level of personalization are more likely to be perceived as useful. Transparency and explainability act on the perceived credibility of recommendations, and transparent and explainable algorithms increase trust. Fairness affects the perceived appropriateness of recommendations; fair recommendations make consumers feel respected, thereby increasing their willingness to accept them [5].

4.1.2.Consumer Characteristics

This has a significant moderating effect on cognitive evaluation. Algorithmic literacy influences cognitive judgment. Consumers with high algorithmic literacy can better understand the recommendation logic and make more objective evaluations. By contrast, consumers with low algorithmic literacy are more susceptible to the surface features of algorithms and make subjective evaluations. Trust propensity also affects cognition: consumers with a high trust propensity are more likely to believe in the appropriateness of recommendations and thus evaluate them positively, whereas consumers with a low trust propensity hold a skeptical attitude and evaluate them negatively [17].

4.1.3.Product Features

This also affects consumers' cognitive evaluation. Product involvement acts on evaluation criteria. For high-involvement products, consumers attach importance to the precision and credibility of recommendations, making their evaluations stricter, whereas for low-involvement products, consumers attach importance to the convenience of recommendations, making their evaluations more lenient. Product complexity also affects cognition: for complex products, consumers are more likely to rely on the support provided by recommendation information, which increases their perceived usefulness. By contrast, for simple products, consumers' reliance on recommendations is lower, and their perceived usefulness is relatively lower [18].

4.2. Emotional Response Mechanism

Emotional response is the affective experience that consumers generate based on cognitive evaluation, mainly including trust, satisfaction, disgust, anxiety, and so on, and it directly affects willingness to accept recommendations and behavioral decision-making.

4.2.1.Trust

This is a core emotional response, referring to the degree to which consumers believe that their needs are satisfied and their rights and interests are protected through recommendations. Its formation is influenced by multiple factors: transparent and explainable algorithmic recommendations reduce perceived risk and increase trust; the accuracy of recommendations raises expectations regarding trust and strengthens it; and an enterprise's brand reputation also increases consumers' trust in algorithms—for example, the higher the brand reputation, the higher consumers' trust in algorithmic recommendations [5].

4.2.2.Satisfaction

This refers to the satisfaction consumers feel regarding the degree of fit between recommendation results and their own needs. The higher the accuracy of recommendations, the greater the degree of fit and the higher the satisfaction. Satisfaction is an important driving

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factor for consumers to continue using the recommendation function and to engage in repeat purchase behavior [12].

4.2.3.Antipathy and Anxiety

Disgust mainly arises from the intrusiveness and irrelevance of recommendations; recommendations that are excessive in frequency and unrelated to needs make consumers feel disturbed. Anxiety mainly arises from privacy risks and uncertainty: consumers worry about privacy leaks caused by algorithms collecting excessive personal data, or feel uncertain about recommendation logic and results. Negative emotional responses trigger consumers' rejection behaviors toward algorithmic recommendation, such as turning off the recommendation function or uninstalling related applications [19].

4.3. Behavioral Decision-making Mechanism

Behavioral decision-making is the consumer's final response to algorithmic recommendations; it represents the specific actions taken based on cognitive evaluation and emotional response. These include accepting the recommendation, rejecting the recommendation, and providing feedback on the recommendation, which directly determines the realization of managerial value.

4.3.1.Accept the Recommendation

This is manifested in consumers' actions, such as clicking on recommended content, purchasing recommended products, and sharing recommended information. These actions are mainly driven by trust and satisfaction: the higher the level of trust and satisfaction, the stronger the willingness to accept the recommendation. In addition, the attractiveness of the recommended content and the price advantages of the product also influence acceptance behavior. The more attractive the content and the more favorable the price, the higher the probability that consumers will accept the recommendation. Such behavior brings enterprises direct benefits in terms of traffic, sales volume, and other indicators [12].

4.3.2.Reject the Recommendation

Such actions constitute negative behavioral decisions and are manifested in measures such as ignoring recommended content, disabling the recommendation function, and blocking recommended information. They are mainly driven by negative emotions such as disgust and anxiety: the stronger the disgust and anxiety, the higher the willingness to reject recommendations. For example, if recommended content is consistently irrelevant and poorly aligned with consumer needs, this significantly strengthens their intention to reject recommendations and may even affect consumers' attitudes toward the company [19].

4.3.3.Providing Feedback on the Recommendation

Specifically, this is manifested in consumers rating recommendations, leaving comments, and sharing them. Such actions provide informational support for algorithm optimization and help enterprises improve recommendation accuracy. The occurrence of this behavior mainly depends on consumers' willingness to participate and perceived value: the higher the willingness to interact and the more consumers believe that feedback will improve recommendation quality, the more willing they are to provide it. In addition, feedback-providing behavior is influenced by the incentive systems adopted by enterprises. Many companies use incentive measures such as awarding points and issuing coupons, which substantially increase consumers' motivation to leave feedback [8].

5. CONCLUSION AND FUTURE RESEARCH AGENDA

Algorithmic recommendations, as a key managerial tool in the era of the digital economy, have profoundly changed the logic of enterprises' marketing management and consumers' decision-

ISSN: 2472-3703 DOI: 10.6911/WSRJ.202611_12(11).0003

making patterns. This paper systematically summarizes the technical properties of algorithmic recommendations and the logic of their fit with managerial scenarios, analyzes in detail their managerial value in improving marketing efficiency, optimizing customer experience, strengthening brand connections, and stimulating product innovation, as well as potential risks including algorithm dependence, algorithmic discrimination, leakage of private data, and ethical controversies. In addition, it reveals the mechanism of consumer responses to algorithmic recommendations at three levels: cognitive evaluation, emotional response, and behavioral decision-making. Overall, further research can be conducted in the following directions.

5.1. Further Research on the Ethical Governance of Algorithms

Algorithmic ethics issues are becoming increasingly prominent and constitute a key factor affecting the sustainable development of algorithmic recommendations. Therefore, future research needs to clarify operationalized definitions and measurement instruments for core ethical dimensions such as privacy, accountability, and algorithmic fairness, and to explore pathways for collaborative governance at three levels: government, enterprises, and consumers.

5.2. Further Research on the Integration Effect of Emerging Technologies

The rapid development of emerging technologies such as artificial intelligence, big data, and blockchain opens up new possibilities for optimizing algorithmic recommendations. Looking ahead, it is necessary to study the application effects and influence mechanisms of generative AI in creating recommended content and optimizing personalized recommendation models, and to explore how blockchain technology can enhance the transparency, security, and fairness of algorithms in order to overcome the crisis of trust in them.

5.3. Further Research on the Long-term Management Effects

Existing research mainly focuses on the short-term managerial effects of algorithmic recommendations, while long-term effects remain insufficiently studied. Looking ahead, it is necessary to focus on the long-term impact of algorithmic recommendations on brand equity and to investigate how brand equity is accumulated and enhanced through mediating variables such as brand trust and brand identity; to analyze how prolonged use of algorithmic recommendations affects consumers' decision-making habits, the formation of their preferences, and their brand loyalty; and to examine how enterprises can build long-term competitive advantages through algorithmic recommendations.

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