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CONSUMER DECISION-MAKING MECHANISMS RECONSTRUCTION BY MEANS OF RECOMMENDATION ALGORITHMS

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This article examines the reconstructive effect of recommendation algorithms on consumer decision-making mechanisms. Based on empirical research from the Netflix platform, it analyzes how recommendation systems reshape user decision pathways through cognitive mechanism manipulation. The research reveals that recommendation algorithms influence user decisions through the dual-system theoretical framework (System 1 and System 2), facilitating a transition from active search to passive acceptance. Through the consideration of global market data and user behavior patterns, the study validates the commercial effectiveness and potential challenges of algorithmic intervention, providing theoretical and practical guidance for the future development of recommendation systems.

Keywords: recommendation algorithms; consumer decision-making; dual-system theory; user behavior; Netflix; cognitive resources.

РЕКОНСТРУКЦИЯ МЕХАНИЗМОВ ПРИНЯТИЯ ПОТРЕБИТЕЛЬСКИХ РЕШЕНИЙ С ПОМОЩЬЮ РЕКОМЕНДАТЕЛЬНЫХ АЛГОРИТМОВ

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В этой статье рассматривается реконструктивный эффект рекомендательных алгоритмов на механизмы принятия решений потребителями. На основе эмпирических исследований платформы Netflix анализируется, как рекомендательные системы перестраивают пути принятия решений потребителями посредством манипулирования когнитивными механизмами. Результаты исследования показывают, что рекомендательные алгоритмы влияют на решения пользователей с помощью теоретической схемы из двух систем (Система 1 и Система 2), способствуя переходу от активного поиска к пассивному принятию. Рассматривая данные глобального рынка и модели поведения пользователей, исследование подтверждает коммерческую эффективность и потенциальные проблемы алгоритмического вмешательства, предоставляя теоретические и практические рекомендации для будущего развития рекомендательных систем.

Ключевые слова: рекомендательные алгоритмы; принятие потребительских решений; теория двух систем; поведение пользователей; Netflix; когнитивные ресурсы.

Introduction. In the digital era, recommendation algorithms have gradually penetrated the core domains of consumer decision-making. This technological revolution has not only transformed the efficiency of information distribution but has also fundamentally reshaped the allocation of human cognitive resources. We observe a significant transformation: consumer decision-making patterns have shifted from active search to passive acceptance, while the decision pathway has been algorithmically compressed into an “intuitive trigger-immediate feedback” closed loop.

The impact of recommendation algorithms on consumer decision-making mechanisms. Recommendation algorithms reconstruct consumer decision pathways by manipulating underlying cognitive mechanisms. Based on Kahneman's dual-system theory, this influence manifests in two dimensions: System 1 (the intuitive system) relies on heuristic rapid responses, such as users' immediate clicks on recommended content, which typically occur at the millisecond level and depend on psychological shortcuts like visual anchoring; System 2 (the rational system) requires cognitive resource investment for cost-benefit analysis, such as subscription plan selection and long-term payment willingness evaluation, but is susceptible to information overload [1]. The dynamic interaction between these two systems determines the efficiency and quality of decision-making, while recommendation technology achieves behavioral guidance through precise intervention in this interaction. Netflix's recommendation system serves as a prime example, successfully converting the intuitive decision-making of System 1 into an "automatic engine" through perceptual stimulus design (such as high-saturation dynamic thumbnails and character facial expression close-ups) and behavioral inertia cultivation (such as the "popular rankings" anchoring effect and auto-play functionality), significantly enhancing conversion efficiency (tab. 1).

Table 1

The dual-system theoretical framework for analyzing Netflix's user decision mechanisms and algorithmic intervention effectiveness

Decision system type	Characteristics	Recommendation algorithm impact mechanism	Performance indicators
System 1 (intuitive system)	• Rapid response • Emotion-driven • Automated processing	• Visual stimulus optimization • Emotional triggers • Immediate feedback	• Click-through rate increased by 30% • Viewing completion rate increased by 25% • Average decision time reduced by 40%
System 2 (rational system)	• Deep thinking • Logical analysis • Cost-benefit assessment	• Information transparency • Comparison tools • User review system	• Subscription conversion rate increased by 15% • Long-term retention rate 93% • User satisfaction increased by 20%

Based on: [2; 3].

The table illustrates the impact of recommendation algorithms on dual-system decision mechanisms and their performance metrics. System 1 (intuitive system), through visual optimization and immediate feedback, achieved significant improvements with a 30 % increase in click-through rate and a 40 % reduction in decision time; System 2 (rational system), through information transparency and evaluation tools, attained a 93 % retention rate and a 20 % enhancement in user satisfaction [3]. This demonstrates that recommendation algorithms have achieved remarkable effectiveness in both rapid decision-making and deep cognitive processing domains.

Data analysis and business effects. The effectiveness of Netflix's recommendation algorithm has been robustly validated through its global market performance (tab. 2).

Data indicates that from 2020 to 2024, the total global user base expanded from 203.66 million to 282.72 million, maintaining a stable annual growth rate within the 8–12 % range. Regional markets exhibited differentiated growth characteristics: North America, as a mature market, achieved robust growth of 14.7 % with a user base reaching 84.80 million; the EMEA region demonstrated strong performance with 44.1 % growth, reaching a user base of 96.13 million; the Latin American market maintained a growth momentum of 31.0 %; while the Asia-Pacific region led global growth with a 106.4 % increase, surpassing 52.60 million users. The recommendation system demonstrated exceptional performance in guiding user behavior, driving 75 % of viewing activities and achieving a 93 % user retention rate, with the "Popular Rankings" feature increasing click-through conversion rates by over 30 %. In emerging markets such as India, through regionalized pricing strategies (20–

60 % price reductions) combined with personalized recommendations, Netflix significantly enhanced market penetration and user engagement levels (tab. 2) [4; 5].

Table 2

Quantitative assessment matrix of Netflix's global market performance and user dynamics

Impact dimension	Quantitative indicators	Growth effect	Business value
User scale	Global user base	203.66M → 282.72M	10% annual growth
Regional distribution	Market penetration	North America +14.7% EMEA +44.1% Asia-Pacific +106.4%	Diversified growth
User behavior	Algorithm-driven rate	75% views from recommendations	Enhanced engagement
Business conversion	Retention rate	93% user retention	Stable revenue stream

Based on: [4; 5].

Based on behavioral tracking research of a one-million-user sample from the Netflix platform, user content consumption decisions exhibit unique spatiotemporal distribution characteristics. Through in-depth analysis of decision timing, user behavior demonstrates a significant bimodal distribution, reflecting differential strategies in cognitive resource allocation. In terms of content exploration pathways, user behavior exhibits a typical "funnel effect", forming a clear conversion pathway from a 42 % homepage click-through rate to a final 23 % viewing completion rate. Notably, the "butterfly effect" exploration pattern shows that one successful recommendation triggers an average of 2.8 consecutive content views [6]. The recommendation acceptance rate displays significant time-dependent characteristics, starting with an 85 % high acceptance rate during the initial phase, then stabilizing at around 70 % after an adaptation period, forming a unique "adaptive dynamic adjustment" pattern [4]. These findings not only deepen our understanding of user decision-making mechanisms but also provide important empirical foundations for recommendation algorithm optimization.

However, the development of recommendation algorithms faces multiple challenges. At the technical level, there is a need to seek balance between efficiency and ethics: on one hand, achieving business objectives through efficient activation of System 1 (intuitive system), while on the other hand, ensuring users' cognitive welfare through rational guidance of System 2 (rational system) [1]. Regarding user experience, platforms need to address information overload issues, avoid filter bubble effects, while protecting users' decision-making autonomy. To achieve sustainable development, Netflix is building a "human-calibrated" mechanism, improving content distribution efficiency through algorithm optimization, reducing user acquisition costs, and establishing a responsible technological development framework [2; 7]. This transformation has elevated recommendation algorithms from auxiliary functions to core business tools, continuously optimizing user value through tiered pricing strategies and high-quality content recommendations, driving overall improvement in platform operational efficiency.

Technical optimization and future development trajectories. The optimization of recommendation algorithms necessitates a delicate equilibrium between operational efficiency and ethical considerations: leveraging the efficient activation of System 1 for commercial objectives while simultaneously ensuring cognitive welfare through the rational guidance of System 2. This equilibrium transcends mere technical challenges, representing a fundamental safeguard for human decision-making autonomy in the digital epoch. Empirical analysis demonstrates the profound impact of recommendation algorithms on consumer behavior patterns, with Netflix's success exemplifying the transformation of algorithms from auxiliary functions to core business utilities. However, the intensified reliance on algorithm-driven decision mechanisms presents potential risks, including cognitive saturation and information filter bubbles. Future developmental trajectories should incorporate a more balanced methodology, ensuring user experience optimization that harmonizes efficiency with ethical considerations. The technological advancement challenge lies in the integration of “human-centric calibration” within algorithmic frameworks, facilitating sustainable growth while preserving consumer decisional autonomy.

Conclusion. Recommendation algorithms have reshaped consumer decision-making mechanisms through precise cognitive process interventions, bringing both efficiency improvements and new challenges. Research indicates that successful recommendation systems need to strike a balance between the rapid response of the intuitive system and the deep thinking of the rational system, while considering algorithmic ethics and the protection of user autonomy. Future development should focus on constructing “human-centered calibration” mechanisms, ensuring user cognitive welfare while enhancing business value. This research provides new perspectives for understanding consumer behavior in the digital age and offers practical guidance for recommendation system optimization.

References

1. *Kahneman D.* Thinking, Fast and Slow. New York : Farrar, Straus and Giroux, 2011. P. 13–24.

2. It’s all about testing: the Netflix experimentation platform [Electronic resource] // Netflix Technology Blog. URL: https://netflixtechblog.com/its-all-a-bout-testing-the-netflix-experimentation-platform-4e1ca458c15 (date of access: 08.02.2024).

3. How Netflix used Big Data and analytics to generate billions [Electronic resource] / Selerity SAS. URL: https://seleritysas.com/2019/04/05/how-netflix-used-big-data-and-analytics-to-generate-billions/ (date of access: 08.02.2024).

4. *Gomez-Uribe C. A.* The Netflix recommender system: algorithms, business value, and innovation // ACM Transactions on Management Information Systems. 2015. Vol. 6(4). P. 1–19.

5. Netflix Financial Reports (2020–2024) [Electronic resource] // Netflix. URL: https://ir.netflix.net/ir-overview/profile/default.aspx (date of access: 08.02.2024).

6. Understanding user navigation patterns [Electronic resource] // Netflix Research. 2023. URL: https://research.netflix.com/research-area/recommendations (date of access: 08.02.2024).

7. How Netflix’s recommendations system works [Electronic resource] // Netflix Help Center. URL: https://help.netflix.com/en/node/100639 (date of access: 08.02.2024).