

Based on the Cooperation between Netflix and Marvel: An Economic Analysis of Film and Television Algorithmic Recommendation on User Stickiness

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Abstract:

In the context of the Internet era, the massive amount of information makes network users face the dilemma of ‘choice overload’, and how to optimise the algorithmic recommendation mechanism to push information accurately has become a new challenge for enterprises. This paper focuses on the characteristics of the film and television industry, taking the cooperation between Netflix and Marvel as the research basis, and analyzes how film and television platforms represented by Netflix enhance user stickiness and competitiveness through algorithmic recommendation mechanisms from an economic perspective. The research aims to explore the impact of algorithmic recommendations on user behavior and satisfaction in the film and television industry. By examining the strategies employed by Netflix, this paper seeks to understand how platforms leverage data analytics and machine learning algorithms to personalise content recommendations. Furthermore, it delves into the economic implications of these recommendation mechanisms, particularly in terms of consumer surplus, information asymmetry, and attention economy. The analysis will provide insights into the effectiveness of algorithmic recommendations in fostering user loyalty and enhancing the overall competitiveness of film and television platforms in the digital age.

Keywords: algorithmic recommendation mechanism; personalised recommendation; attention; attention economy; Netflix

1. Introduction

1.1 Research Background

In recent years, the global film and television industry has undergone a profound digital transformation. With the rapid development of Internet technology, the popularisation of 5G networks, and the mature application of cloud computing, big data, and other technologies, the production, dissemination, and consumption models of film and television content have been disruptively transformed. Traditional cinema and TV broadcasting models have gradually migrated to online streaming media. Platforms such as Netflix, Disney+, and iQiyi have emerged, and by the end of 2023, the global streaming media user base exceeded 1.5 billion, making digitisation and networking the mainstream trend of the industry.

In this context, algorithmic recommendation mechanisms are widely used to solve the problem of ‘choice overload’—platforms build personalised recommendation models by mining data such as users’ historical viewing behaviours and search records. For example, Netflix accurately delivers content based on user preferences, which not only improves users’ efficiency in accessing high-quality content but also serves as a core means for platforms to enhance user stickiness and market competitiveness. It is worth noting that in the digitalisation process of the industry, user attention resources have become a scarce economic factor. The essence of platform competition is the competition for ‘user time currency’, while user stickiness (such as viewing duration and payment conversion rate), as a core economic indicator of profit models such as streaming media subscription revenue and advertising monetisation, the correlation between it and algorithmic recommendation urgently needs to be analysed from an economic perspective.

“In the future, the value of information (the stuff being produced) would trend toward zero, while the value of attention, which is owned by consumers but can be leveraged by companies that help them allocate it, would only rise.”[1]

Based on this, this study analyses the algorithmic recommendation cases in the film and television industry around the key resource of ‘attention’ and proposes suggestions for the industry to improve user stickiness. Among many cases, the cooperation between Netflix and Marvel has typical economic research value: the strong fan economic attributes of Marvel’s IP make sticky data such as re-watch rate and rating distribution highly quantifiable, and customised content such as Daredevil and algorithmic recommendations form a closed loop of ‘supply-demand matching’, providing an ideal scenario for analysing sup-

ply-demand side interactions.

The innovations of this paper are mainly reflected in: (1) constructing a closed-loop causal model of ‘recommendation mechanism-user behaviour-platform benefit’, which opens up the theoretical chain between micro-level user stickiness and platform economic value; (2) for the first time combining consumer surplus theory with empirical evidence of IP recommendation, proposing a ‘low cost-high surplus’ content supply mechanism; (3) in the context of the attention economy, proposing the path of ‘algorithm-driven optimisation of attention resource allocation’, providing a theoretical basis for digital platform stickiness construction strategies.

1.2 Research Purpose and Significance

1.2.1 Theoretical Significance

This study constructs an economic analysis model of ‘algorithmic recommendation-user stickiness’, filling theoretical gaps in the field of film and television economics from three aspects. Based on consumer surplus theory, it analyses how algorithmic recommendations of film and television platforms enable users to obtain excess utility at lower attention costs by accurately matching user preferences, and quantifies the utility increment brought by personalised recommendations; with the help of information asymmetry theory, it reveals that recommendation systems alleviate ‘choice difficulties’ under content overload by constructing label systems; based on attention cost theory, it explains that algorithmic recommendation mechanisms maximise the marginal benefits of users’ time and attention resources by dynamically adjusting recommendation weights, extending the average viewing duration. This model innovatively embeds classical economic theories into the analysis of algorithmic recommendation mechanisms, breaking through the limitation of existing research that focuses on technology rather than economics, and providing an innovative theoretical framework for analysing the resource allocation logic behind ‘attention monetisation’.

1.2.2 Practical Significance

Taking the cooperative content of Netflix and Marvel as an empirical object, this study analyses the algorithmic recommendation mechanism of the film and television industry combined with economic models, and provides economical and practical reference plans for film and television platforms to optimise recommendation strategies based on the theoretical foundations of consumer surplus and attention cost, helping enterprises enhance user stickiness and market competitiveness.

2. Literature References

In recent years, research in the field of recommendation systems has focused on algorithm optimisation and cross-domain applications. Wei Huan (2013) proposed improving the LFM model by fusing labels and film and television ontology in *Research on Movie Personalised Recommendation Algorithm Based on Ontology*[2], improving recommendation interpretability and real-time performance through label interest calculation and ontology label cleaning. Zhang Shujuan (2024), in *Research on Integrated Marketing Communication from the Perspective of 'Eyeball Economy'*[3], emphasised from the perspective of attention economy that integrated marketing communication needs to accurately reach the audience and maximise communication effects through multi-channel synergy. Ming Andong (2021) proposed improving the THACIL model in *Research on Personalised Recommendation Algorithm for Short Videos Based on Attention Mechanism*[4], simplifying the time-level attention mechanism, introducing user interest attention, reducing model complexity, and improving recommendation efficiency. *E-commerce Website Recommendation System Based on Improved Collaborative Filtering*[5] proposes the ICFR algorithm, which optimises the real-time performance and accuracy of recommendations in e-commerce scenarios by incrementally updating user preference data and improving PCC similarity calculations. However, existing research mainly focuses on the technical level, and the analysis of algorithmic recommendation mechanisms from an economic perspective is still relatively lacking. This paper takes the cooperation case between Netflix and Marvel as a sample, combining consumer surplus and information asymmetry theories to analyse how algorithmic recommendations realise commercial value transformation through the chain of 'IP value-algorithm matching-user stickiness'.

3. Theoretical Foundation and Research Framework

Attention, originally a psychological term, refers to a cognitive process of humans, which is the orientation and concentration of mental activities on a certain object. In the information age, attention has become a scarce resource, and its effective allocation can create economic

benefits. User stickiness reflects a product's ability to maintain continuous user use, reflecting the degree of user dependence and loyalty. Based on the following three theories, this paper analyses how algorithmic recommendation mechanisms of film and television enterprises such as Marvel and Netflix enhance user stickiness and maximise attention benefits.

3.1 Consumer Surplus Theory

Proposed by Marshall at the end of the 19th century, consumer surplus refers to the difference between the actual price paid by consumers and the highest price they are willing to pay. Based on the law of diminishing marginal utility, this theory reveals the extra benefits consumers obtain in transactions, providing a basis for enterprise pricing and personalised recommendation strategies. This paper takes the pricing strategy of Marvel's IP derivative works as an example to analyse how enterprises expand consumer surplus and enhance user stickiness through algorithmic recommendations.

3.2 Information Asymmetry Theory

Akerlof put forward the information asymmetry theory in *The Market for Lemons* [6] in 1970, which refers to the failure of the market mechanism caused by one party in a transaction holding more information. This theory breaks the assumption of 'complete information', explains the root cause of market failure, and provides ideas for modern institutional design. In this paper, we will discuss how the platform can act as an information intermediary to alleviate user screening costs in the Netflix personalised recommendation mechanism.

3.3 Attention Cost Theory

Attention cost is the cost of time, energy, and opportunity for individuals to focus on cognitive resources. In the era of information overload, enterprises reduce user screening costs through personalised recommendations to gain a competitive advantage. This paper will combine with Netflix's algorithmic recommendation interface design to analyse how film and television enterprises can cut users' attention cost and improve users' retention rate by optimizing the recommendation mechanism.

Based on the above theoretical foundation, the research framework of this paper is proposed as table 1 showing:

Table 1. Economic Analysis Framework for Enhancing User Stickiness

through Algorithmic Recommendation

Analysis Dimension	Key Theory	Corresponding Mechanism	Impact on User Behavior	Platform Economic Effect
Optimization of Supply-Demand Matching	Consumer Surplus Theory	The platform identifies user preferences via algorithms and delivers highly relevant content	Reduces time costs and provides psychological excess utility	Enhances user stickiness and boosts renewal rates
Improvement of Information Screening Efficiency	Information Asymmetry Theory	The recommendation system constructs content tags, classifies and presents them to minimize selection costs	Decreases search behavior, elevates viewing efficiency and satisfaction	Increases platform interface conversion rate and optimizes content exposure
Allocation of Attention Resources	Attention Cost Theory	Dynamically adjusts recommendation weights to concentrate users' attention on high-value content	Prolongs dwell time, raises re-viewing rate and completion rate	Improves advertising monetization capability and user lifetime value

4. Case Background and Analysis of Algorithmic Recommendation Mechanism

4.1 Case Background: A brief analysis of the content features of Netflix and Marvel's cooperation

From 2015 to 2019, Netflix and Marvel launched an in-depth cooperation, launching several series such as Daredevil, Jessica Jones, Luke Cage, etc., extending the Marvel universe from the big screen to the small screen. This cooperation not only brought new superhero stories to Marvel fans but also made Netflix stand out in the streaming media competition.

As a top global IP, Marvel has a huge and highly loyal fan base, with a significant fan economy effect. These fans have a high re-watch rate for Marvel works and are keen to repeatedly savour plot details and explore Easter eggs, which brings stable traffic to Netflix. At the same time, Netflix, with its powerful algorithmic recommendation system, can deeply analyse user preferences based on viewing history, ratings, and other data, and customise episodes that match audience interests, thereby improving user stickiness. For example, based on users' love for dark-style superhero stories, it created Daredevil, which is full of darkness and struggle. This perfect combination of IP value and algorithmic recommendation mechanism forms a supply-demand closed loop—IP attracts users, algorithms retain users, and user needs feed back into content creation.

Under this cooperation model, this study focuses on how IP content accurately matches user interests with the help of algorithms to maximise content value and commercial value, providing a valuable reference model for subse-

quent cooperation between streaming media and IP.

4.2 Brief Analysis of Recommendation Mechanism

Netflix mainly achieves accurate content delivery through collaborative filtering algorithms and reinforcement learning. The collaborative filtering algorithm analyses interaction data between users and items (such as ratings, clicks, purchases, etc.) to identify users or items with similar behavioural patterns, and then makes recommendations based on these similar relationships.

Netflix's most valuable asset is its algorithmic recommendation mechanism, including rating prediction, ranking algorithms, data, and models. Based on billions of rating information, combined with the analysis of users' historical behaviours and similar audience behaviours, it generates a personalised recommendation list for each user. For example, through Item-Based collaborative filtering, it identifies content with high co-occurrence with Daredevil (such as Agents of S.H.I.E.L.D., Daredevil), and defines users who have watched such content as 'superhero core audiences'. On the other hand, it uses DRN (Deep Reinforcement Network) to dynamically adjust recommendation strategies. For example, if a user clicks on the Daredevil trailer but does not watch it, the system will reduce the weight of subsequent recommendations and try to push clips of similar series for 'interest awakening'. If a user watches the first season in its entirety, the system will increase the recommendation priority for the second season and associate recommendations for The Defenders. Through the above precise and personalised algorithmic recommendation, the platform effectively solves the problem of information redundancy, simplifies the user selection process, improves the user's satisfaction with the platform in the process of using it, and thus effectively

enhances user stickiness.

4.3 User Stickiness Enhancement Mechanisms: an Economic Explanatory Framework

4.3.1 Consumer Surplus Theory

Consumer surplus theory reveals the difference between the highest psychological price consumers are willing to pay for goods or services and the actual payment cost, which is essentially the excess utility users gain from transactions. Taking *Daredevil* as an example, the core fan base of Marvel IP has a clear preference for ‘dark hero’ themes, and their psychological willingness to pay is significantly higher than that of ordinary series. Netflix provides *Daredevil* and Marvel Universe-related content through a monthly subscription service of \$15.99, and the actual fixed cost paid by fans is much lower than the premium they are willing to pay for exclusive content—both in terms of the economic cost of purchasing copyrights individually and the time cost of screening through massive content.

In this process, consumer surplus is generated through a dual mechanism: on the one hand, algorithmic recommendations accurately match *Daredevil* with users’ historical viewing data, allowing fans to reduce content search time costs and obtain target content at a lower ‘attention cost’, significantly improving psychological utility; on the other hand, the series activates fans’ deep emotional identity with the Marvel universe through designs such as implanting The Avengers timeline Easter eggs and character linkages. The emotional satisfaction brought by this ‘closed-loop content experience’ further expands the gap between psychological willingness to pay and actual cost, promoting Netflix to attract core audiences with a ‘low cost-high surplus’ strategy, forming a positive feedback of ‘IP customisation-accurate recommendation-surplus accumulation’, and reshaping the decision-making logic of the film and television consumer market: users no longer measure value only by content unit price but pay more attention to whether the platform can maximise their consumption surplus through algorithms and IP ecosystems, thereby promoting the industry’s transformation from single-content transactions to a model of ‘efficient attention resource allocation’.

4.3.2 Information Asymmetry Theory

In the recommendation process of *Daredevil*, Netflix fully utilises the key role of an ‘information intermediary’ through information asymmetry theory. On the one hand, there is serious information asymmetry in the film and television market. Users find it difficult to fully understand the characteristics of *Daredevil* in terms of text, visual

dimensions, metadata, etc., and it is also difficult to accurately locate works that match their interests in massive content; on the other hand, user behavioural data also has asymmetry—users cannot quantify their viewing preferences, while Netflix deeply mines users’ explicit feedback (ratings, likes) and implicit behaviours (viewing duration, search records) through full-scene behavioural tracking to establish accurate user profiles.

Based on the information asymmetry advantage between content and users, Netflix maps the multimodal characteristics of *Daredevil* to the global interest label system, and then achieves seamless access to highly compatible users through personalised recommendations, significantly reducing users’ information screening costs, bridging the information gap, and reshaping the information balance of film and television content consumption.

4.3.3 Attention Economy Theory

In the era of the eyeball economy, the continuous emergence of massive information has made attention a scarce resource. In 1997, American scholar Michael Goldhaber pioneered the ‘Attention Economy’ theory in *Attention Shoppers*[7]. The core idea of this theory is that in the context of information overload, attention, like money, has liquidity and can be directly converted into economic benefits. This theory is vividly reflected in the film and television industry, where major film and television platforms compete for audience attention by creating high-quality content to increase platform traffic, boost economic returns, and consolidate their position in fierce market competition.

Netflix’s algorithmic recommendation mechanism is a model of in-depth practice of the ‘attention economy’ theory. It uses dynamic weight recommendation strategies, comprehensively considering user behavioural data, content characteristics, and real-time trends, committed to accurately matching user interests with film and television works. Taking the recommendation of the Marvel IP series *Daredevil* as an example, the system carefully analyses users’ preference for Marvel IP, past viewing history, and other multi-dimensional data, and then dynamically adjusts the priority and display mode of *Daredevil* in the recommendation list. This precise recommendation strategy can effectively extend users’ stay time on the platform, improve content consumption efficiency, and significantly increase the ‘attention investment return rate’.

By comparing the data of IP series (Marvel corporation) and non-IP series, as table 2 shown, we can more clearly see the practical effect of attention economy theory in Netflix’s algorithmic recommendations. In terms of average ratings (IMDb), IP series scored 7.2, while non-IP series only scored 5.8. Higher ratings indicate that the IP

series has advantages in content quality or appeal, capable of attracting more audience attention. Algorithmic recommendations have a significant impact on the completion rate of IP series on Netflix: the completion rate of recommended users is as high as 68%, while that of non-recommended users is only 32%. This shows that algorithmic recommendations successfully capture users' attention by accurately matching user interests, greatly increasing the

possibility of users completing the series. In addition, in terms of average viewing duration after recommendation, IP series are 47 minutes, much higher than the 19 minutes of non-IP series, once again confirming the strong ability of IP series to attract and retain user attention, and reflecting the important role of Netflix's algorithmic recommendations in optimising attention resource allocation.

Table 2. Comparison of User Behavior Data between IP Drama Series (Marvel Collaboration) and Non-IP Drama Series on the Netflix Platform

Comparison Dimension	IP Drama Series (Marvel Collaboration)	Non - IP Drama Series
Average Rating (IMDb)	7.2	5.8
Completion Rate of Algorithm - Recommended Users (Netflix)	68%	—
Completion Rate of Non - Recommended Users (Netflix)	32%	—
Average Viewing Duration after Recommendation (Netflix)	47 minutes	19 minutes

(Data Sources: Publicly available film and television rating database of IMDb; Publicly available user behavior analysis reports of the Netflix Platform and industry research institutions)

4.4 Summary

This chapter takes Netflix and Marvel cooperation episodes as the object, combines the operation logic of the recommendation mechanism with user behaviour data, and dissects the mechanism of algorithmic recommendation to enhance user stickiness from the three aspects of consumer residual optimization, information intermediary function, and attention resource allocation. The study verifies the core role of algorithmic recommendations on platform user value enhancement and builds a logical foundation for the subsequent conclusion chapter.

5. Conclusions and Recommendations

5.1 Main Conclusions

This paper combines consumer surplus, information asymmetry theory, attention cost, and other economic principles, based on the content of the cooperation between Marvel and Netflix in-depth analysis of how the film and television platforms use an algorithmic recommendation mechanism to effectively improve user stickiness, and then improve their own competitiveness in the market. Netflix mainly through the matching of demand and supply, information screening, and allocation of attention resources to reduce the user's choice cost. Netflix reduces the user's selection cost and realizes accurate promotion

to the high-fit user group.

5.2 Theoretical Contributions

The breakthroughs of this paper at the theoretical level are mainly reflected in three aspects: firstly, it expands the economic interpretation perspective of algorithmic recommendation research, and incorporates the technology-driven recommendation mechanism into the analysis framework of consumer behaviour, which fills in the research gaps between traditional economic theories and the platform's technological mechanism; secondly, it constructs a 'recommendation mechanism - user behaviour - platform benefit' approach. - Secondly, it constructs a closed-loop path model of 'user behavior - platform benefit', systematically explaining the dynamic influence mechanism of algorithmic recommendation on user decision-making and platform value creation; thirdly, it innovatively integrates the three major theories of consumer surplus, information asymmetry, and attention economy into an analytical paradigm, which provides a cross-sectional perspective for algorithmic optimization and business strategy formulation in the streaming media industry.

5.3 Platform Operation Suggestions

5.3.1 Platform Side Optimisation Strategies

Platforms should strengthen the two-way insight capability of users and content. On the one hand, it should build dynamic user profiles based on user behavioral data (viewing history, search keywords, interaction frequency, etc.) and achieve group stratification through cluster analysis; on the other hand, it should conduct multi-di-

mensional gene disassembly of IP content, extract key elements such as theme tags, visual styles, and narrative features, and establish an intelligent matching model between the content and user preferences. At the same time, it is recommended to set up an IP ecosystem linkage recommendation system, which automatically associates and pushes IP content of the same universe by monitoring users' in-depth behaviours towards specific IPs (such as re-watching rate, egg search and character discussion), promoting users' closed-loop consumption of content on the platform, and enhancing users' overall reliance on the platform's IP ecosystem.

5.3.2 Strategies for IP Operation

In the IP operation dimension, the platform can innovate business models based on consumer surplus theory. Firstly, design 'IP combo subscription package', differentiate the head IP and long-tail content bundling, reduce the content screening cost with a price strategy lower than users' psychological expectation, and expand the space of consumer surplus; secondly, implement a dynamic pricing mechanism, targeting high-frequency IP users (e.g., Comic Book fans with more than 10 hours of monthly viewing time). Secondly, implement dynamic pricing mechanism, precisely push exclusive paid content or value-added services to high-frequency IP users (e.g. Marvel fans who watch more than 10 hours per month), to achieve stepwise growth of ARPU value through user stratification; finally, encourage cross-media narrative and derivation development of IP content, and strengthen synergistic effect of different forms of content (series, comics, games) through algorithmic recommendation, to prolong the life cycle of IP and the chain of user value.

5.4 Research Limitations and Future Directions

There are certain limitations in this study: the data source mainly relies on public data of Netflix and industry reports, which lacks the support of platform-level full-volume data, which may affect the universality of the research conclusions; the theoretical analyses focus

on specific IP cooperation cases, and the extrapolation of theories in the context of pan-entertainment needs to be further verified; the study focuses on the perspective of economics. The theoretical analysis focuses on specific IP cooperation cases, and the extrapolation of the theory in pan-entertainment scenarios needs to be further verified. Future research can be carried out in three aspects: first, to obtain multi-platform and multi-type data to build a cross-case comparative analysis model; second, to integrate the theories of communication and sociology to improve the multi-disciplinary explanatory framework of algorithmic recommendation; and third, to combine the user experience and technology dismantling to explore the complex path of the algorithmic mechanism's influence on users' behaviours.

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