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Countermeasures for Enhancing User-Generated Content on Short Video Platforms Through Recommendation Mechanisms

Xue Mingxin[1,a,*]

[1]*Department of Information Systems, City University of Hong Kong, 83 Tat Chee Avenue, Kowloon, Hong Kong*
a. mingxixue2-c@my.cityu.edu.hk
**corresponding author*

Abstract: The proliferation of short video applications and platforms has paralleled the growing popularity of this media format. In the increasingly competitive landscape of short-form video, companies have adopted numerous strategies to expand their market share, retain active users, and ensure sustainable platform operations. Among these strategies, one of the most pivotal is the utilization of recommendation mechanisms and algorithms to personalize video suggestions for users. For platform users, the additional traffic and exposure facilitated by recommendation mechanisms present a valuable opportunity for their videos to reach a wider audience. This paper delves into the characteristics and commonalities of user-generated content on video platforms influenced by recommendation algorithms, and examines the strategies employed by video creators to harness the increased traffic and exposure provided by these mechanisms, as well as the dynamics between users and the platform. We have randomly selected video data from the "Beeping Beeping" pop-up website for analysis. The study also scrutinizes the actions taken by video producers to exploit the resources and opportunities provided by the recommendation mechanism. Furthermore, it explores the interactions between users and the platform. To carry out this research, we selected a sample of twenty random videos from each of the ten video producers who boast a substantial fan base on the "Bleeping.com" website. While the recommendation mechanism simplifies the user experience, it simultaneously offers varying resources and opportunities to different users. Users who comprehend the platform's recommendation guidelines and underlying algorithms can proactively leverage the mechanism to aid in video creation and dissemination. This approach enables them to actively promote high-quality user-generated content on the video platform during the video creation and upload phases.

Keywords: short video, recommendation, algorithm, personalized recommendation, user-generated content

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1. Introduction

1.1. Research Background and Significance

1.1.1. Research Background

The rise of short video as a means of communication coincides with the proliferation of internet terminals, enhanced network speeds, and the emergence of the internet celebrity economy. Short videos have gained favor with numerous platforms and capital investments due to their distinct features of clear information, concentrated content, and concise communication. In recent years, the user base of short videos has continued to grow. According to the 49th "China Internet Development Status Statistical Report" released by the China Internet Network Information Center (CNNIC), as of December 2021, the user base for short videos had reached 934 million people, with a utilization rate of 90.5%. It is projected to reach 985 million users by December 2022, with a utilization rate of 92.4%.

The convenience of mobile terminals has led people to favor devices like smartphones and tablets for video consumption. Mobile short video applications are becoming the mainstream video social platforms for netizens. For instance, TikTok, one of these platforms, had an active user base of 671.8 million people in December 2021. Both content viewers and creators are numerous, with a continuous influx of original videos into the platform's vast content pool. The order and method by which videos enter users' field of vision within this extensive pool significantly affect a video's viewership, likes, and comments.

Simultaneously, for users watching videos, the abundance of data and information presented in video format makes finding specific information or preferred content challenging. To address potential issues related to information overload and filter bubbles, video platforms and application developers utilize algorithms for content filtering and recommendation. This not only saves users time in searching for videos but also provides platforms with an understanding of their user base. In the highly competitive short video market, one of the key strategies employed by major operators is the development of more precise recommendation systems compared to their competitors and content providers.

Conversely, content creators aiming to build a substantial fan base on various platforms and sustain high viewership need to have a comprehensive understanding of the platform's content push mechanisms and rules. With this knowledge, they are more likely to receive high traffic and platform recommendations.

1.1.2. Research Significance

With the short video trend sweeping through social platforms and mobile applications, users on video platforms not only include those who upload videos to document their lives but also a substantial number of professional video creators. These creators rely on the income generated from their video uploads as a primary source of livelihood, significantly contributing to the development of the short video economy. Over time, creators who regularly publish videos on video platforms and maintain a certain update frequency attract a stable fan base that follows and subscribes to their channels, becoming regular viewers. These viewers contribute to the continuous increase in platform views.

For viewers, if they consistently see videos of interest to them on the platform's recommended page, they gradually increase their platform usage frequency. To compete for more active users, platforms and app developers have introduced video recommendation mechanisms and algorithms to create user profiles for content recommendation. Current recommendation mechanisms are capable of collecting user information from multiple dimensions, enhancing the accuracy of video recommendations to target users. Videos with high relevance to the interests of related users have a better chance of entering a larger content pool, increasing the likelihood of receiving higher views, likes, and comments compared to similar video creators. Creators accumulate followers, achieve profitability, and become more enthusiastic about video creation as their videos are recommended more frequently. As the number of successful recommendations for their videos increases, the creators are more inclined to create and publish more content, attracting more followers. As the user base for watching and creating videos on the platform increases, platform user activity also rises. Hence, the use of mature video recommendation mechanisms is a win-win for both the platform and users. However, as algorithms are not infallible, there is a risk of high-quality user-generated content not receiving matching high traffic or being recommended to users with low relevance, resulting in a potential loss of a significant number of loyal users.

Recommendation and filtering algorithms determine the types of videos viewers can access and browse on websites and app platforms. For most video platforms and short video applications, the primary objective for companies is to grow their user base, leading them to periodically update and improve their algorithms. Users can speculate and determine the reasons why their uploaded videos are either recommended or restricted.

This paper endeavors to analyze the impact of recommendation algorithms on user-generated content, focusing on content with high views and likes produced by top creators on the Bilibili video platform. It aims to assist users in increasing the probability of their user-generated content being recommended after upload while examining potential issues in the bi-directional interaction between the platform and its users.

1.2. Research Methods and Innovations

1.2.1. Research Methods

Literature Review: Prior to the paper's composition, an extensive review of relevant literature was conducted. This process involved browsing and reading numerous pertinent documents to acquire an understanding of the current research status and existing theories within the field. This laid a strong theoretical foundation for the paper.

Case Study: This paper selects short video content published on Bilibili as the subject of analysis. A computer program was employed to randomly select ten users from the top 500 non-platform official accounts based on their follower count. Twenty videos from each of these ten content creators' personal pages were collected, totaling 200 videos as the sample data for this study. An analysis of the video content was conducted, focusing on aspects such as the content's theme, video tags, participation in activities, and engagement in trending topics. Based on the analysis of the sample data, the paper further illustrates that user-generated content tailored to the platform's traffic distribution and recommendation logic receives more visibility to users, thereby guiding individual users to produce content more aligned with the platform's technical recommendations.

1.2.2. Innovations in Research

The innovation in this paper lies in its research perspective. Most existing studies concerning video platforms and user-generated content primarily revolve around the creative behavior of video content creators, whether such behavior occurs, the reasons behind it, and the influencing factors. In contrast, this paper's focal point is the examination of how users, under the influence of recommendation mechanisms, respond when generating content and the information shielding or filter bubble issues that may arise within the bi-directional interaction between the platform and its users. Building on the research findings, recommendations are provided to both the platform and users.

2. Related Research and Theoretical Foundation

2.1. Current Research Status

This paper primarily investigates the recommendation mechanisms and algorithms of video platforms, the responses of users to these mechanisms in their quest for increased exposure and traffic, and the presentation of user-generated content. Therefore, the literature review in this paper focuses on two main aspects: recommendation algorithms and mechanisms, as well as user-generated content.

2.1.1. Research Status on Recommendation Algorithms and Mechanisms

In the era of fragmented information and explosive data growth, video platforms are striving to capture a limited user base and enhance user retention. They employ personalized video recommendation mechanisms to improve user experience and satisfaction. Different video platforms have adopted varying mechanisms and algorithms for video recommendations. Recommendation algorithms are a technological field built on data analysis and information filtering mechanisms, allowing for intelligent matching of information within the platform to the users.

Traditional recommendation algorithms generally fall into two categories: content-based recommendation algorithms and collaborative filtering recommendation algorithms. These two types of algorithms rely on content-based information filtering and collaborative filtering technologies. Collaborative filtering technology complements content-based information filtering technology. Content-based recommendation algorithms center around constructing descriptive models, extracting textual information and data about content, and calculating the similarity between user preferences and product content characteristics. Recommendations are made by comparing the similarity between users and products. In the early stages of recommendation technology, content-based recommendation algorithms were the most widely used across various fields, including early news platforms, e-commerce platforms, and video websites. The core idea of collaborative filtering algorithms is to use historical user information to calculate the similarity between users, identify users with the highest similarity to the target user (the most similar users), and predict the target user's preference for specific products based on the ratings provided by the most similar users. Recommendations are made to users based on their preference levels. Unlike content-based recommendations, collaborative filtering algorithms do not require specific attributes from recommended objects and can handle resources of any type, even those that are difficult to textually describe.

Both domestic and international research on recommendation algorithms and mechanisms has generally focused on associating rules with algorithms, dissecting algorithm limitations, and proposing optimization solutions to enhance algorithm efficiency and recommendation quality. These efforts often involve combining multiple algorithms to design more precise mechanisms that cater to individual user preferences. In addition to the two primary algorithms mentioned above, many scholars have ventured into researching and designing hybrid recommendation algorithms to address more complex real-world issues.

In the paper "User Behavior-Based Video Recommendation," Zhu Luwei built a user rating recommendation system using the SCVD model on the basis of model-based collaborative filtering. This approach incorporates users' personalized demands into the model [1]. Researchers such as Yang Wu have studied a fused recommendation method that combines content-based and collaborative filtering approaches. This method not only caters to individual user preferences but also effectively avoids temporal lag associated with mixed recommendation methods [2]. Scholars like Zhang Runlian proposed a collaborative filtering algorithm based on hybrid similarity and differential privacy to address privacy leakage concerns. They improved the recommendation precision by

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calculating weighted hybrid similarity through multiple similarity measures [3]. Wang Yonggui and Li Xin introduced the concept of fuzzy clustering membership in the context of item-based collaborative filtering algorithms. They used the wolf pack algorithm to enhance the accuracy of finding similar users [4]. Additionally, scholars including Ma Xin put forward an enhanced algorithm, CPDFC-CFR (Category Preferred Data Field Clustering-Based Collaborative Filtering Recommendation). This algorithm abandons user ratings and introduces the concepts of category preference and semantic preference. It aims to reduce data sparsity while improving recommendation accuracy and computational efficiency [5]. These innovative ideas and algorithms continually provide various approaches to existing issues within the field of recommendation systems.

The aforementioned algorithms and computational logic represent the most commonly used recommendation algorithms on mainstream video platforms. With a basic understanding of algorithm mechanisms, video creators often adopt various measures to maximize their opportunities within these mechanisms. These creators enrich the platforms with original content and take actions to align their video content with algorithmic recommendations. Viewers of videos are frequently subjected to opaque recommendation mechanisms. In most cases, they primarily browse recommended videos on their feed, as opposed to explicitly searching for videos based on specific themes or keywords. Consequently, such users are susceptible to being trapped in filter bubbles created by recommendations and algorithms. In contrast, content creators adjust and modify their video content based on a general understanding of recommendation algorithms to attain higher traffic and mitigate this issue.

Zhang Yaping, in a study on self-presentation of short video users under the influence of algorithmic recommendations, highlighted that algorithmic intervention provides a reference for users in content production but simultaneously limits the scope of their content production. The interplay between algorithms and user behavior can result in issues such as content duplication and homogenization. To address these issues, a collective effort from platforms and video creators is required [6]. Examining short video user-presented content from the perspective of algorithmic recommendations can, to some extent, provide users with insights into self-awareness.

2.1.2. Research on User-Generated Content (UGC)

User-Generated Content (UGC) is currently a significant source of information for various online platforms. Combining existing research, Wang Jimeng has defined UGC broadly as any content created and published by ordinary users on internet content production platforms in the form of text, images, audio, and videos, among other formats [7]. In terms of research trends, both domestic and international studies have primarily focused on the behavior of users creating content on video websites and the impact of such content on consumers. In contrast, domestic research mainly centers on the motivations of short video users' content creation and the factors influencing UGC's impact on social e-commerce.

The main focus of this paper is the user-generated content on video platforms. In recent years, major social platforms have accelerated their strategic expansion into the social short video domain. Short video has become one of the most popular and well-received forms of social interaction in the internet age, combining content creation and sharing. For video websites and platforms, high-quality content within UGC is their core competitive advantage. Furthermore, UGC, as compared to PGC (professional-generated content), possesses inherent genetic advantages, as it is characterized by noticeable heterogeneity and has a lower threshold for creation. Video creators face no technical barriers and can easily become the main driving force behind video platform content creation. However, even though UGC has promising prospects, numerous studies have shown that UGC poses challenges and issues due to its inherent attributes and characteristics that need to be addressed.

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Chen Xin and others conducted a characteristic analysis of UGC on YouTube and identified the "long-tail" phenomenon within UGC systems. This phenomenon suggests that only a small portion of the videos published on a website is genuinely viewed by the majority of users, while the remaining videos receive fewer views. This issue, primarily affecting the long-tail segment, can lead to network congestion, redundancy, and low storage space efficiency within video systems if less popular videos fail to become profitable assets [8].

Regarding the analysis of motivations for video user-generated content, Li Zhen conducted a comprehensive examination of various factors influencing user content creation behavior. The study revealed that user content creation motivations are complex and encompass external incentives and internal user factors. Both factors collectively influence the initiative and enthusiasm of users in content creation [9]. Additionally, Fei Xin developed a model and conducted empirical research based on the dimensions of motivation, opportunity, and ability. The research indicated that on short video platforms, the entertainment value of short videos, their usefulness, users' sense of belonging within the platform's community, and their individual creative abilities all have a positive impact on user content creation. The emergence of virtual online communities also fulfills users' social needs. When content creators experience a sense of respect and self-value realization in the social process, their content creation is further encouraged [10]. Chen and other researchers have demonstrated that the interaction between users and user-generated content forms a dynamic cycle. They developed a quantitative modeling method based on empirical data concerning the growth dynamics of User-Generated Content Sharing Networks (UGCSNets). In UGC-centered shared network platforms, video creators serve as both content providers and users. To create a healthy dynamic cycle within UGCSNets, the participation and mutual promotion of video creators and the platform are essential [11].

In summary, algorithms have found extensive applications in the short video domain, enabling users to discover videos of interest. Current research on algorithms primarily focuses on technical and ethical aspects, with fewer discussions on the combined use of algorithms, users, and video content. Moreover, research on short videos and user-generated content often centers on motivations for video production and pays less attention to the impact of algorithm mechanisms on user-generated content. Under the influence of video recommendation algorithms, it is essential to understand how user-generated content is affected and what measures can be taken to improve and optimize recommendation mechanisms and user-generated content. These aspects are the main research focus of this paper.

2.2. Relevant Theories

2.2.1. Algorithm Logic of Short Video Recommendation Mechanism

This study focuses on sampled video data from Bilibili Danmaku (B 站弹幕) website. The recommendation mechanism algorithm of Bilibili Danmaku includes a hybrid recommendation algorithm that combines content-based recommendation algorithms and collaborative filtering algorithms. The model is designed to extract, analyze, and mine information and data from user-generated content, such as video categories, tags, and themes. It also uses historical user interactions and records on Bilibili Danmaku to extract user features. The collaborative filtering algorithm is then employed to find users with high similarity to the user's interests and recommend videos that the user might find appealing. When users visit the recommendation page, videos are recommended based on the matching of user features and video content, considering factors like user engagement, likes, coins, collections, follows, shares, dislikes, and disinterest. Recommendations are presented to users in the form of a list, and the recommendation system continually optimizes results based on user feedback, aiming to provide better and more accurate recommendations.

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2.2.2. Main Process of Short Video Recommendation Mechanism

In the past, when the user base was smaller, Bilibili Danmaku relied on manual recommendations instead of algorithms. However, with the platform now serving millions of users, the platform no longer uses the older single-label classification system such as "二次元" (2D) and "非二次元" (non-2D). Instead, its mechanism's rules involve providing an initial flow of views to a video, followed by subsequent rounds of recommendations based on user feedback, including metrics like view counts, likes, and comments. As users engage with content and provide feedback, the system iteratively fine-tunes recommendations to match content with user preferences.

When a video creator on Bilibili Danmaku uploads an original video, it undergoes initial machine review. If the video content doesn't violate any rules or laws, it passes the machine review and is eligible for platform promotion. However, if it doesn't pass the machine review, it enters manual review for confirmation. After the two-step review process is completed, the video enters the recommendation process. Initially, the video is recommended to a smaller audience. The first round of small-scale recommendations typically occurs within three hours after the video passes review. The second round of recommendations, targeting a larger audience, happens approximately seven hours after review. After these two rounds of recommendations, the platform's algorithm assesses the video's popularity and quality. Popularity is evaluated based on metrics like likes, coins, collections, shares, comments, and danmaku interactions, while video quality is determined by how many people, among 50 targeted users sharing the video's tags, clicked on and completed watching the video. Following machine evaluation, high-popularity and high-quality videos proceed to further recommendations. For each additional like, a video may be recommended to ten more users. Conversely, for videos with lower popularity, the platform performs a third, smaller-scale recommendation about 13 hours after the video review. If a video's popularity remains low, no further recommendations are made.

Bilibili Danmaku's recommendation process not only incorporates machine algorithms but also features manual recommendations. In various categorized sections, if a video's popularity doesn't meet the traffic evaluation criteria but it maintains high quality, human editors confirm the video's thematic relevance and content quality, providing manual recommendations for high-quality content. In addition to daily fixed recommendation processes, Bilibili Danmaku motivates users to create content through occasional thematic incentive activities. During these events, editing videos that meet the activity criteria can result in extra exposure and cash rewards. Videos created for these activities receive priority recommendations over non-participating videos in the same category.

Compared to short video platforms like TikTok that prioritize algorithms, Bilibili Danmaku has its shortcomings in terms of algorithm technology. However, Bilibili Danmaku's human editors play a crucial role in content distribution. They utilize their extensive work experience and deep understanding of users, communities, and content to provide recommendations that align closely with user preferences and fit the platform's style. Bilibili Danmaku's recommendation mechanism and policies tend to favor "potential" content creators in their early stages, as the platform's selection and support of emerging creators can accelerate their growth. As Bilibili Danmaku is a platform with strong fan engagement, non-professional content creators aiming to gain steady traffic support are required to ensure both the consistency of video uploads and the high quality of content.

3. User-Generated Content and Creative Behavior on Video Platforms: A Case Analysis

3.1. Sample Selection and Basic Sample Information

In this study, user-generated content from Bilibili Danmaku website was chosen as the data collection target. Python software was employed for data retrieval. A total of 10 top content creators (referred

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to as "famous uploaders" on Bilibili Danmaku) who are not official platform accounts were randomly selected. These content creators have a significant fan base, with each being among the top 500 in terms of the number of followers. From each of these famous uploaders accounts, 20 videos were randomly selected for analysis, resulting in a dataset of 200 videos. The basic information of the selected famous uploaders accounts is presented in Table 1:

Table 1: Basic Information of 10 Selected famous uploaders Accounts

Username	Number of Followers	Account Section	Number of Videos Published	Total Likes on Account
Xiaopianpianshuodapian	6.3 million	Film and TV	1304	77,320,000
Wooden fish water heart	10.19 million	Film and TV	1229	63,154,000
Film hurricane	5.85 million	Film and TV Knowledge	586	34,918,000
Movie TOP	4.98 million	Film and TV	507	23,347,000
Daoyueshe food encounter	7.59 million	Food	529	79,428,000
A hardcore half-Buddha	7.16 million	Lifestyle	391	70,822,000
Ouyang Chunxiao Aurora	4.542 million	Sports	173	10,284,000
Xingyouye	4.19 million	Animation	107	41,952,000
HelloTeacher I am He	10.86 million	Science and Technology	48	45,878,000
Sheep cooking	10.829 million	Food	354	72,276,000

3.2. Analysis of Sample Video Content

In relation to the primary focus and theme of this study, the article provides a more detailed analysis of the sample video content, specifically in terms of content themes, video tags, participation in platform activities, and involvement in popular topics.

3.2.1. Analysis of Sample Video Content Themes

Upon analyzing the content themes of randomly selected video samples, it is evident that videos with high likes and coin counts are generally those where content creators provide rich and distinct viewpoints. In sections such as Film and TV and Animation, high-quality user-generated content involves reinterpretation and re-editing of original content. In the Food section, high-traffic videos showcase the process of food preparation and food reviews, while the Knowledge section typically requires informative and engaging content to captivate platform users.

The majority of the sampled videos are characterized by content creators with unique, substantial, and engaging viewpoints. This indicates that on Bilibili Danmaku, viewers are keen on acquiring knowledge and information while enjoying video content. Therefore, the quality of the videos and the alignment of content creators' viewpoints with audience preferences become crucial factors in determining a video's ability to gain traction and recommendation opportunities. Content creators' unique viewpoints and expressions within their content also play a significant role in establishing a core audience that is not easily replaced by creators in the same category. Long-term consistency in delivering content within a specific domain leads to the accumulation of a relatively fixed fan base. For example, the 20 videos produced by the sampled famous uploaders "绵羊料理" focus on the creation of exquisite and creative dishes, accompanied by engaging narratives. This content consistently attracts an audience interested in the culinary field, maintaining a stable theme and content quality. "绵羊料理" can quickly accumulate views, likes, comments, and bullet comments, triggering the platform's recommendation mechanism and fostering a positive feedback loop, which, in turn, attracts more new fans and makes them regular viewers.

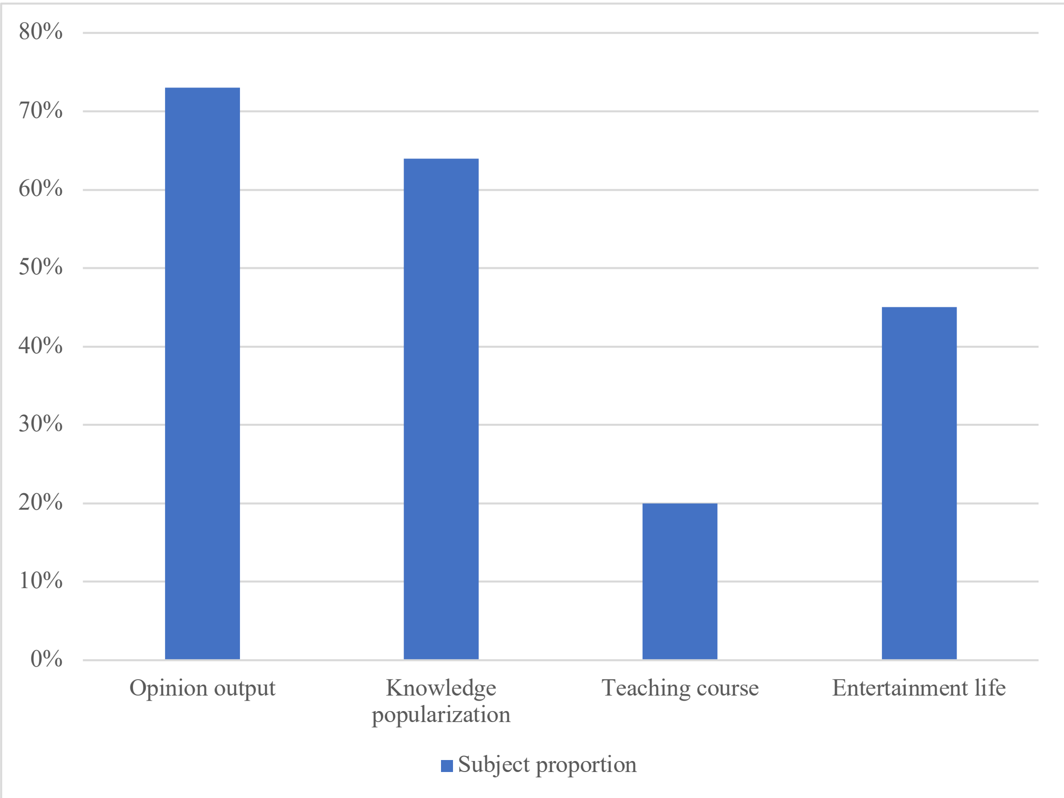

Figure 1: Analysis of Sample Video Content Themes

3.2.2. Analysis of Sample Video Tags

Video tags are a widely used method for content creators on UGC platforms to provide custom information. Tags serve the purpose of summarizing and identifying video content, reflecting content creators' evaluation and genre definition. On Bilibili Danmaku, up to ten different tags can be selected when publishing a video. The use of tags is a way for video creators to position the video theme and simplify the search process for users.

In the selected video samples, the majority of content creators use tags to their full capacity, with eight out of the ten sampled famous uploaders using all ten different tags for each of their videos. Bilibili Danmaku allows users to customize and add tags, as well as use existing ones. The system recommends tags based on the video's title. Most tags function equivalently to entering tag text into the Bilibili homepage's search bar. Some existing tags correspond to Bilibili's section or subsection names. For example, the tag "电视剧剪辑" (TV Series Editing) belongs to the subsection "影视剪辑" (Film and TV Editing) under the section "影视区" (Film and TV). Using such tags that correspond

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to sections or subsections increases the chances of being discovered by users interested in a particular area, enhancing the likelihood of clicks. Moreover, some tags appear as both regular tags and channels simultaneously, indicated by a triangular icon formed by three dots in front of the tag. This occurs when the tag represents both a channel and a section or subsection. Adding a video to a channel is automatic and cannot be initiated by users. The system identifies it, and when the popularity of a regular tag reaches a certain threshold, it automatically becomes a channel. Users can subscribe to channels to track content related to a specific theme.

For the specific tag content analysis, 85% of the video tags in the sampled videos contain at least one channel, while 91% are names of sections or subsections. This indicates that content creators who have achieved head famous uploaders status on the platform have a high frequency of tag use, and they utilize tags as an effective means to gain traffic through the recommendation mechanism. This demonstrates their understanding and mastery of platform mechanisms and dissemination patterns.

3.2.3. Analysis of Participation in Platform Activities in Sample Videos

Bilibili Danmaku conducts numerous incentive activities every day. Participating in such activities allows content creators to engage with viewers in specific fields, and these activities often offer traffic rewards. In the video samples, 64% of the videos participated in these activities. Taking part in these activities allows content creators to reach viewers in their areas of interest, and for those who have not yet accumulated many followers, it's an opportunity to have their quality work promoted through the platform's traffic support. For content creators with a substantial following, participating in activities can attract new followers interested in their field.

Each activity corresponds to a traffic pool where users can select to participate. For selected videos, these traffic pools filter out irrelevant or cumbersome information, ensuring that they are more accurately matched with target users.

3.2.4. Analysis of Participation in Popular Topics in Sample Videos

In the video tags editing page, users have the option to choose whether to join discussions on popular topics. This is separate from the ten tags added by users during content creation and does not count in the tag number. In the video samples of the ten famous uploaders, nine of them engaged in discussions on popular topics. Across all video samples, 35% of videos participated in discussions on popular topics. This relatively low participation rate can be attributed to two reasons. Firstly, the emergence of popular topics is not controlled by the platform but rather is related to recent social events and media attention. Therefore, some famous uploaders in specialized niches may find it challenging to connect with popular topics if their domains do not easily intersect with widely-discussed themes. Secondly, popular topics have a strong temporal aspect, and there could be cases where a video creator intends to produce content related to a popular topic but by the time the video is produced and uploaded, the topic is no longer in trend. Participation in popular topics is manifested in the platform's recommendation mechanism and process through users' concentrated interest in a particular area of a topic. Content highly relevant to popular or widely-discussed topics is more likely to be recommended to users' homepages.

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4. Research and Analysis of User-Generated Behavior and its Impact under the Influence of the Recommendation Mechanism

4.1. Common Characteristics of Platform's Top Video Creators and Strategies for Video Creation

4.1.1. Common Characteristics of Platform's Top Video Creators

An analysis of videos created by top famous uploaders (content creators) reveals that within the same genre, user-generated content that stands out in a sea of homogeneous content tends to possess certain characteristics. These characteristics include high content quality, low substitutability, strong interactivity, and content continuity.

High content quality and low substitutability are the most basic requirements for top famous uploaders. In the initial stages of account operation, creating multiple high-quality videos is essential to gain the attention of a large number of platform users. Leveraging the interactive nature of Bilibili Danmaku, content creators and viewers can engage through comments and bullet comments. In the analyzed video samples, both comments and bullet comments are significantly higher compared to similar videos. In terms of bullet comments, the most interactive videos in the sample maintain an 8:1 ratio of video views to bullet comments. This implies that for every eight users who click to view a video, one interacts with the content through bullet comments. Content continuity is reflected in the logical connection between user-generated content. Some video creators have a habit of previewing the content of the next video, and users interested in the topic will continue to follow subsequent videos out of curiosity and a desire for knowledge. This naturally increases user engagement and may even convert users into fans when creators produce video series.

4.1.2. Strategies Employed by Video Creators to Adapt to the Recommendation Mechanism

Analysis of the video samples selected for this study reveals that experienced video creators can grasp the general rules of the platform's recommendation mechanism. They make adjustments and modifications during key stages of content creation to align with the recommendation mechanism. The recommendation algorithm and mechanism influence two aspects of video creation: the video production process and the video upload process.

In the video production process, video creators in the sample adopt measures to utilize the recommendation mechanism, including:

Crafting video themes and content in line with public hot topics to make their videos more accessible to other users during searches and to participate in discussions on popular topics. Proper use of tagging functionality enhances exposure.

Increasing the percentage of original content duration within videos by introducing thought-provoking viewpoints that stimulate discussions and keep viewers engaged. High viewer retention is crucial as it is a key metric for evaluating video popularity and quality. Videos with high completion rates, even if they start with low initial traffic, have the potential to be discovered and recommended through manual processes.

During the video upload process, video creators employ platform mechanisms in the following ways:

Using the platform's tagging feature to provide precise information to users, increasing the likelihood of their content being discovered. While selecting tags, creators consider the inclusion of section and subsection names, ensuring videos are automatically categorized in homepage section blocks during the user's initial filtering process. They may also choose to add channel names as Bilibili Danmaku users can subscribe to channels. This helps video creators push their videos to the homepages of loyal users in related domains.

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Including discussion keywords related to popular topics when video content aligns with such topics. Increased exposure leads to higher play rates.

Participating in platform incentive activities. The platform's traffic support for participating content creators helps generate more traffic during algorithmic and manual recommendation stages.

Maintaining a steady output at regular intervals. Among the selected video creators, 90% are capable of maintaining a stable and rapid video production and upload rate. This aids in sustaining popularity within a particular domain as top famous uploaders with numerous fans. Quality content is key, but the ability to create and promote high-quality content is continuously evolving. Relying solely on a few high-traffic videos may not effectively attract users to become their permanent fans, which makes it difficult for accounts to operate and grow in the long term during the initial recommendation phase.

4.2. Limitations of Algorithm Mechanisms and Their Impact on User-Generated Content, as well as Incentives

4.2.1. Limitations of Algorithm Mechanisms and Their Impact on User-Generated Content

Algorithm mechanisms are designed and employed to accurately match content with users and deliver high-quality content to their homepages. However, the inherent limitations of algorithm mechanisms can restrict users from accessing diverse and comprehensive information. The mechanisms primarily base their recommendations on a user's historical data and recent users with similar interests. As a result, users may find it challenging to explore domains and information they have not previously engaged with. The algorithm has the power to dictate what kind of information users can access, thereby influencing users' knowledge boundaries. Over time, users' recommendation interfaces and personal homepages may be confined to algorithm-defined interest categories, further narrowing their viewing choices. This phenomenon does not foster cultural dissemination and information exchange; it, in fact, encourages user differentiation and group formation. Furthermore, users who become fatigued by viewing similar content themes may abandon the platform, increasing the risk of user attrition.

4.2.2. Incentives of Recommendation Algorithms and Mechanisms for Video Creators

Algorithm mechanisms provide incentives for video creators' creative activities. With lowering technical barriers, the previous limitations have been removed, and contemporary video platforms empower all users to create content, record their lives, and express their viewpoints through videos. The presence of mobile devices and the ability to create content regardless of time and place free users from constraints. The recommendation mechanism aids users in finding like-minded individuals and those with shared interests within the platform's community. Video creators can showcase their user-generated content to other users with the assistance of recommendation algorithms. Compared to past mechanisms that merely displayed videos, the introduction and promotion of recommendation algorithms assure users that their videos won't be buried among an overwhelming sea of data and videos. If creators receive feedback and ratings from viewers, they are incentivized to continuously improve the quality of their user-generated content and create new high-quality works.

On video platforms, the number of views determines the upper limits of likes, coin counts, and favorites. Likes, coin counts, and favorites can be converted into cash earnings for video creators. The recommendation algorithm provides exposure to video creators, indirectly increasing their potential income. This is a significant reason why famous uploaders continue to create content.

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5. Incentive Measures by the Platform Based on the Recommendation Mechanism

After researching the impact of the video platform's recommendation mechanism on user-generated content, this study found that users take various measures and actions to adapt and maximize the platform's resources and traffic to achieve their goals. Conversely, the video platform can respond based on the behavior of video creators and users who watch videos. When there is competition among video creators for limited resources, the platform should prioritize the promotion of high-quality videos as its primary task. Regardless of whether video creators understand the platform's recommendation mechanism or not, the platform should allocate a certain amount of traffic to avoid high-quality videos being eliminated by the mechanism during the initial recommendation process. This prevents the loss of excellent video creators. Thus, the platform should control the latter from excessively occupying the former's traffic and promotion channels by exploiting the mechanism's rules.

The paper explores the characteristics of user-generated behavior and the strategic interactions among video creators under the recommendation mechanism. The platform should respond to these strategies and engage positively with users, rather than providing rigid mechanisms and traffic allocation. Since users' understanding and awareness of the recommendation mechanism vary, the extent to which users utilize the video platform's recommendation mechanism also differs. To ensure that the circulation of videos is not restricted by the existence of the recommendation mechanism, the platform should take proactive measures to promote the long-term and stable development of the platform in collaboration with users who watch and create/upload videos.

Establishing a positive dynamic interaction between video platforms and video creators can prompt timely updates and optimizations of platform mechanisms. Therefore, based on the analysis of user-generated content and the behavior of video creators, this paper offers valuable recommendations for the video platform. Recommendations are divided into two categories: measures for video creators on the platform and measures for non-video creator users on the platform. Since the impact and effects of the recommendation mechanism differ for these two types of users, recommendations for both are provided as follows:

5.1. Recommendations for Measures Targeted at Video Creators on the Platform

To help the platform employ a more efficient recommendation mechanism, companies and platforms that introduce the recommendation mechanism into their daily promotion activities should continually monitor user feedback. Based on user behavior and the current state of recommendations, the following recommendations are offered to platforms using the recommendation mechanism to improve the user experience for video creators and viewers:

When creating specialized tags and pages for "channels" and "hot topics," avoid setting attention, search volume, and other factors as the sole criteria. Instead, create dedicated channels for niche topics. This provides users who are interested in niche hobbies and videos with an interface and public channels to upload and watch videos, diversifying platform content.

Prioritize limited exposure opportunities and promotion channels for newly uploaded videos. According to the existing video recommendation mechanism and algorithms, once a video is deemed excellent based on metrics like likes and comments, the video is repeatedly recommended to users' homepages. However, high-quality videos that haven't received widespread attention for various reasons need the assistance of the recommendation mechanism to boost their traffic, especially when their popularity has reached certain levels, like a million views or a hundred thousand likes. Therefore, the priority of recommending such videos should be reduced, allowing videos with high alignment to users' interests and lower popularity, but judged to be excellent in the manual review stage, to be prioritized for recommendation.

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The platform should deeply understand the reasons behind video creators' measures and address the shortcomings in the platform's recommendation mechanism. It should establish an instant feedback mechanism, making recommendation opportunities and traffic support available to as many users as possible. This will prevent top famous uploaders with numerous followers from dominating the vast majority of traffic due to their follower aggregation effect, which is detrimental to new creator support and long-term platform operations.

Some editorial functions should be retained. After the first round of recommendations, quality checks of videos should be handed over to human editors to avoid low-quality videos with high initial popularity from disproportionately occupying traffic at the expense of high-quality videos. This helps maximize the efficiency of network platform resource usage.

After enhancing the recommendation mechanism, the platform can increase transparency for video creators. This encourages more users to engage with the platform's recommendation mechanism, improving interaction and trust between the platform and users. The platform should actively create channels and spaces for dialogue and communication.

5.2. Recommendations for Measures Targeted at Non-Video Creator Users on the Platform

Platform users can be divided into two main groups: those who create and upload videos and those who only watch videos. In the process of video creators actively responding to the recommendation mechanism, users who primarily watch videos will inevitably be influenced. Since the algorithms of the recommendation mechanism and the videos created by video creators affect the content users can access, if the platform cannot guide video creators to produce high-quality videos and select efficient and accurate algorithms, it is likely that users will be lost because the recommended content does not match their needs and preferences. This can negatively impact the platform's development. Therefore, based on the analysis of the platform mechanism and video creators' content generation, the following recommendations are provided to ensure a good user experience for users who primarily watch videos on the platform:

Although algorithms rely on technology for recommendations, there are inherent biases in the algorithm design process. Platform designers should strive to avoid algorithmic concentration on popular topics and discrimination against niche topics. Cater to the interests and viewing experiences of users who have niche interests.

To evaluate the effectiveness and user experience of the updated recommendation mechanism, video platforms should design and distribute surveys for users who mainly watch videos. Collect feedback and suggestions from users to understand the functionality they expect from a recommended service when accessing video websites.

When designing the homepage of the website or mobile application, place channels in a more prominent location. For example, in the case of Bilibili Danmaku, the sections and channels on the mobile application are not very visible. Users who are not familiar with the app or cannot use it proficiently may find it challenging to access sections they are interested in for video browsing. They may instead click on the recommended videos, leading to a gradual limitation in the variety of videos users are exposed to. Over time, the platform's recommendations may become monotonous and unexciting to users. To address this, the platform should take measures or encourage users to select sections and channels under these sections themselves to enhance the diversity of content on the platform and help algorithms collect user information more extensively to improve their precision.

The recommendations provided aim to help the platform understand and clarify the needs of different user groups. Video creators hope to have their videos seen by more people and generate real income. Especially for full-time famous uploaders, apart from the traffic a single video can garner, these video creators must also consider the ongoing operation of their accounts. Thus, they need to maintain continuous exposure for their accounts and a stable output of videos. For active non-creator users on the platform, who only watch videos, their hope is to broaden their knowledge and have a good video viewing and social experience on the platform. They expect the platform to continuously recommend videos that match their interests and have substantial content. In the realm of video platforms and mobile applications, there are numerous competing products users can choose from. More accurate algorithms mean a better user experience, and this is why major video platforms should continuously update and optimize their algorithms.

6. Conclusion

In this era of information explosion, algorithmic recommendation technology has addressed the dual challenge of bidirectional matching between content and platform users. With the rise of mobile devices, pure algorithmic techniques in video applications no longer hold value and emotional preferences. However, due to the varied interests and content generation habits of different video creators, there is differentiation in the viewership of user-generated content when it enters the first round of distribution and recommendation within the platform's recommendation mechanism. Through a series of filtering processes within the recommendation mechanism, user-generated content is pushed to the homepages of users who the algorithm deems suitable. Throughout this process, users have the option to actively compete for traffic and exposure opportunities, securing resources and channels as a priority. This paper briefly analyzes the commonalities and characteristics of user-generated content and the responses and practices of video creators under the influence of recommendation algorithms and mechanisms.

At present, recommendation technologies and algorithms still maintain an aspect of the "black box" for users. Even though users can have a general perception and conjecture about the algorithms based on patterns and recommendation results, there is still a need for platforms to enhance the transparency of algorithms. On one hand, this openness ensures user privacy and security, and on the other hand, it helps users avoid falling into information bubbles and narrowed perspectives. Users should keep up to date while using the platform, maintain a proactive learning attitude, adjust their attitudes and practices toward user-generated content, and enhance their sensitivity to algorithms, mechanisms, and platform operational rules. This allows them to break free from one-sided algorithmic control, make reasonable use of the recommendation mechanism and algorithms, and harness these mechanisms for their benefit.

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