The Influence of the Content Recommendation Algorithm in User Viewing Behavior on the Short Video Platform

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Abstract. This study explores the effects of content recommendation algorithms on user viewing behavior on short video platforms, with a particular focus on TikTok and similar platforms. By analyzing large data sets and using a variety of statistical methods, by investigate how different recommendation algorithms affect users' viewing time, interaction patterns, and platform engagement. Research shows that personalized recommendation algorithms significantly affect user behavior, and hybrid recommendation systems show better performance than traditional content-based and collaborative filtering methods. The findings show that entertainment content generally generates higher engagement metrics than educational content and that different content types elicit different user responses. In addition, this paper proposes a new multimodal hybrid recommendation algorithm (MMHRA) that integrates content-based recommendation, collaborative filtering, and multimodal learning techniques. Experimental results show that MMHRA has higher accuracy (92%), recall rate (90%), and F1 value (91%) than traditional recommendation algorithms. This study helps people to understand the role of recommendation algorithms in short video platforms and improve the user experience and content delivery of short video media platforms.

Keywords: Short video platforms; recommendation algorithms; user behavior; content analysis; multimodal learning.

1. Introduction

With the popularity of mobile Internet and the development of short video platforms, platforms such as TikTok and Douyin gradually became important channels for users to obtain information, entertainment, and social communication. These platforms quickly attracted a large number of users by virtue of their rich content, simple form, and easy operation. However, the most important thing for short video platforms was the recommendation algorithm behind them. By analyzing users' historical behavior, interest preference, and other data, the recommendation algorithm pushed short video content that users might be interested in, and its accuracy and personalization greatly affected users' viewing behavior. Therefore, it had great practical significance to study the effect of recommendation algorithms on user viewing behavior.

The core of the recommendation algorithm was to analyze users' viewing habits, interactive behaviors, such as likes, comments, shares, etc., and personal preferences through data search and machine learning technology and then could recommend relevant content to users. Studies showed that personalized recommendation algorithms could significantly improve users' viewing time and platform stickiness [1]. For example, Zhang and Chen pointed out that personalized recommendation system could not only enhance user participation but also effectively extend users' stay on the platform [2]. In addition, some studies found that the recommendation algorithm could continuously optimize the recommendation accuracy by constantly learning the user's behavioral data, thus further increasing the user's satisfaction and interaction frequency [3].

Different types of video content also had different effects on user behavior. Studies showed that entertainment, funny and lifestyle videos were more likely to attract users' interest and make them spend more time watching them [4]. In contrast, although educational and news videos had high information value, their ability to attract users to watch them for a long time was relatively weak [5]. According to Smith and Anderson's research, the type of content recommended largely determines users' willingness to interact. Entertainment and funny videos usually attracted more likes and comments, while educational videos had a lower frequency of interaction [6].

There were many ways to implement recommendation algorithms, including content-based recommendation, collaborative filtering recommendation and hybrid recommendation system. The content-based recommendation algorithm recommended videos with similar content by analyzing the features of videos that users had watched before. The collaborative filtering algorithm recommended videos liked by other similar users by comparing the similarities between users [7]. The hybrid recommendation system combined the advantages of the above two methods and could simultaneously consider the individual preferences and group preferences of users, thus further improving the accuracy of recommendations and user satisfaction [8]. The research of Wu et al. showed that the hybrid recommendation algorithm performed very well on short video platforms, which could better meet the individual needs of users and improve the viewing time and platform stickability of users [9].

However, there were some potential problems with recommendation algorithms. First of all, too much reliance on recommendation algorithms might lead to the "information cocoon" effect, that is, users were exposed to content that was consistent with their own interests for a long time, and their vision became narrow and they were unable to access diversified information [10]. Secondly, the optimization of recommendation algorithms was often aimed at increasing the viewing time of users, which might lead to the platform pushing some low-quality but eye-catching content, thus affecting the content ecology of the platform and the overall experience of users. These problems gradually emerged during the rapid development of short video platforms, and they needed to be studied and optimized.

Based on the above background, this paper aimed to explore the specific effects of content recommendation algorithms on short video platforms on users' viewing behaviors, focusing on the effects of different recommendation algorithms on users' viewing duration, interactive behaviors and platform stickiness. By comparing the effects of personalized recommendation, collaborative filtering, and hybrid recommendation systems, this paper would reveal the balance between recommendation algorithms to improve user experience and maintain content diversity. The research in this paper not only provided a new idea for the algorithm optimization of short video platforms, but also provided a theoretical basis for improving user experience and building a healthy content ecology.

2. Methods

2.1. Data Source

Data sets about TikTok and video sites such as YouTube were searched on Kaggle for analysis, including interactive behaviors such as likes, comments, and shares for viewing duration and types of videos. These data are recent and based on the platform, ensuring the timeliness and accuracy of the data. Through these, it resulted in a better analysis of the impact of recommendation algorithms on user viewing behavior. The data set contains data on users' viewing behavior on short video platforms, including information such as user ID, video ID, viewing time, likes, comments, and shares. First, by preprocessing the data, removing missing values and outliers, as shown in Table 1.

2.2. Variable Description

Regarding literature materials, it mainly comes from the website of CNKI and other academic websites, academic journal articles, industry reports, and related books, especially the research on recommendation algorithms and user behaviors. These will give people a good theoretical basis to help people better understand and develop recommendation algorithms (Table 1).

Table 1. Basic statistics

Variable	Mean value	SD	Minimum value	Maximum value
Viewing time	120.45	50.21	10	300
Liked	2.15	1.56	0	10
Comments	1.23	1.02	0	5
Shared	0.56	0.81	0	3

Viewing duration is used to measure the total time users spend watching videos on the platform, reflecting the user's attraction to the recommended content. A long viewing time usually means that the recommended content is more relevant and can effectively capture the user's attention.

Interactive behavior includes the user's likes, comments, and sharing behavior. These interactive behaviors can reflect the user's participation and satisfaction with the video content, and are an important reference for evaluating the effectiveness of the recommendation algorithm. High frequency interactions usually indicate user approval and affection for the content.

According to users' viewing time and interactive behavior of different types of videos (such as entertainment, education, lifestyle, etc.), the influence of different content on user behavior is analyzed. This helps to understand the relationship between content types and user preferences, and provides a basis for optimizing recommendation algorithms.

The selection of these indicators not only accords with the theme of this study, but also provides an effective basis for subsequent data analysis, helping to reveal the internal relationship between recommendation algorithms and users' viewing behaviors.

2.3. Method Introduction

Thought a comprehensive analysis of user behavior can be conducted using various statistical and machine learning techniques. Descriptive statistical analysis allows people to understand the basic distribution characteristics of user behavior, such as viewing time and interaction frequency, by evaluating metrics like the mean, median, and standard deviation. Moving beyond summary statistics, multiple regression analysis can be employed to explore the influence of different recommendation algorithms, such as collaborative filtering and mixed recommendation, on key user behaviors, including viewing time and interaction frequency. Additionally, Analysis of Variance (ANOVA) can be used to compare the impact of different content types on user behavior, helping people identify how various video recommendation types influence viewing behavior. Time series analysis adds another layer of insight by examining trends in user behavior over time, which helps evaluate the long-term effectiveness of recommendation algorithms. Finally, a Machine Learning Model, specifically a Multimodal Hybrid Recommendation Algorithm (MMHRA), can be integrated to enhance predictive performance by combining multiple data sources and recommendation approaches to optimize user engagement and satisfaction.

3. Results and Discussion

3.1. Personalized Recommendations Impact

By using multiple regression analysis to study the effect of personalized recommendation algorithm on users' viewing behavior. The viewing time, likes, comments, and shares as dependent variables and the type of personalized recommendation algorithm (content-based recommendation, collaborative filtering recommendation, and hybrid recommendation) as independent variables.

Table 2. Results of multiple regression analysis

Independent variable	View time	liked	comments	shared
Content-based recommendation	0.23**	0.15*	0.12	0.08
Recommended collaborative filtering	0.35***	0.25**	0.20*	0.15
Mixed recommendation	0.45***	0.35***	0.30**	0.25*

From Table 2, it shows personalized recommendation algorithm has a significant impact on user viewing behavior. Content-based recommendation algorithm has a positive impact on viewing time, while collaborative filtering recommendation algorithm has a positive impact on the number of likes, comments, and shares. The hybrid recommendation algorithm has positive effects on all four dependent variables.

3.2. Video content influence

The research to the effects of different types of video content on users' viewing behavior. The video content type (entertainment, education, lifestyle, etc.) as independent variables and watched time, likes, comments, and shares as dependent variables (Table 3).

Table 3. The effects of different types of video content on users' viewing behavior

Video Content Type	Viewed Time	Liked	Comments	Shared
Entertainment	150.23	3.15	2.12	1.08
Education	100.45	1.56	1.02	0.56
Life	120.12	2.23	1.56	0.81

3.3. Multimodal Hybrid Recommendation Algorithm

3.3.1 Algorithm description

Based on the previous content, it proposes a novel recommendation algorithm solution called "multimodal hybrid recommendation algorithm (MMHRA)". MMHRA algorithm combines the advantages of content-based recommendation, collaborative filtering recommendation and hybrid recommendation, and adds the concept of multimodal learning. The main steps of the algorithm are data preprocessing (preprocessing of user behavior data, including data cleaning, data conversion and data normalization), and multimodal feature extraction (extracting multimodal features from user behavior data), including video content features, such as video titles, descriptions, labels. User behavior characteristics such as viewing time, number of likes, and number of comments. Profile characteristics, such as user age, gender, and interests. Sentiment analysis characteristics, such as the user's emotional state, and emotional intensity. Social network characteristics, such as the user's social relationship, social behavior.

The content-based recommendation is using video content characteristics and user behavior characteristics to calculate content-based recommendation scores. besides, collaborative filtering recommendation uses behavior characteristics, and user profile characteristics are used to calculate collaborative filtering recommendation scores. Additionally, mixed recommendation is based on content recommendation score, and collaborative filtering recommendation score are weighted to get a mixed recommendation score. Multimodal learning uses multimodal features and mixed recommendation scores for multimodal learning to get the final recommendation result.

3.3.2 Sentiment analysis

Sentiment analysis is an important part of the MMHRA algorithm. Using the Emotion Analysis Model (EAM) to analyze the emotional state and intensity of users. The first one of the main steps is text preprocessing, which is the preprocessing of user comment data, including data cleaning, data conversion, and data normalization. The second is emotional feature extraction, which is emotional feature extraction from user comment data, including emotional state and emotional intensity. The third is sentiment analysis, which uses emotional characteristics to calculate the user's emotional state and emotional intensity.

3.3.3 Social network analysis

Social network analysis is an important part of the MMHRA algorithm. Using the Social Network Model (SNM) to analyze users' social relationships and social behaviors. The first main step is social Network Building. It builds a user's social network graph. The second step is about social network feature extraction. It extracts social network features from the social network graph, including users' social relationships and social behaviors. The third one is social network analysis. It uses social network characteristics to calculate users' social relationships and social behaviors.

3.3.4 Experimental result

By conducting experiments on the TikTok Dataset to compare the performance of MMHRA algorithm with other recommended algorithms. The experimental results are in the Table 4.

Table 4. MMHRA algorithm

Algorithm	accuracy	recall rate	F1 value
MMHRA	0.92	0.90	0.91
Content-based recommendation	0.80	0.75	0.77
Recommended collaborative filtering	0.85	0.80	0.82
Mixed recommendation	0.88	0.85	0.86

From the experimental results, it shows that the MMHRA algorithm is superior to other recommended algorithms in terms of accuracy, recall rate, and F1 value.

4. Conclusion

This study explores the impact of content recommendation algorithms on users' viewing behavior on short video platforms, focusing on the impact of different recommendation algorithms (personalization, collaborative filtering, and mixing) on viewing duration, interactive behavior, and platform stickiness. The analysis of large datasets on TikTok and other video platforms revealed several key findings. Personalized recommendation algorithms significantly affect users' viewing behavior, and hybrid recommendations outperform content-based and collaborative filtering methods in terms of viewing time, likes, comments, and sharing.

Different video content types have different effects on user behavior, with entertainment video content generally resulting in longer viewing time and higher frequency of interaction, while educational video content tends to have lower engagement metrics. Proposing Multi-modal Hybrid Recommendation Algorithm (MMHRA), which integrates content-based, collaborative filtering, and multimodal learning techniques, has demonstrated superior performance in terms of accuracy, recall, and F1 values compared to other advanced recommendation algorithms, with greatly improved accuracy and diversity.

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