

How Recommendation Algorithms Influence What We Watch Online

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Abstract: *Online video platforms provide access to an extremely large amount of digital content, making it difficult for individual users to manually search and evaluate all available videos. Recommendation algorithms address this problem by predicting which content a user may find relevant, interesting, or engaging and by ranking that content in a personalized feed. This paper examines how recommendation algorithms influence what people watch online, with particular attention to personalization, viewing history, user interactions, content characteristics, popularity, ranking, and feedback mechanisms. The study uses a narrative literature review based on academic research and selected first-party platform documentation. Existing research shows that large-scale recommendation systems commonly use multiple stages to reduce a very large content catalogue to a smaller set of potentially relevant items. User activities such as watching, skipping, liking, sharing, following, and searching can provide signals that influence future recommendations. These mechanisms can improve content discovery and reduce the effort required to find relevant material, but they may also reinforce existing interests, increase the visibility of popular content, and affect the diversity of content encountered by users. Evidence concerning filter bubbles, polarization, and algorithmic amplification is more complex than the assumption that recommendation systems completely determine user behaviour. Therefore, recommendation systems should be understood as part of a continuous interaction between users and algorithms rather than as systems that completely control viewing decisions. Future research should evaluate recommendation systems using multiple dimensions, including engagement, satisfaction, diversity, transparency, user autonomy, and long-term effects.*

Keywords: Recommendation Systems, Recommender Algorithms, Personalized Video, Machine Learning, User Behaviour, Content Discovery, Algorithmic Curation

I. INTRODUCTION

The rapid growth of digital video platforms has significantly changed the way people discover and consume media. Traditional television generally required viewers to choose from a limited number of channels and programmes that were scheduled in advance, whereas online platforms provide access to enormous and continuously changing collections of content. Recommendation systems have consequently become an important mechanism for filtering and organizing digital content [5]. A recommendation system attempts to estimate which items may be relevant or interesting to an individual user. These predictions can be based on previous viewing behaviour, searches, likes, shares, follows, viewing duration, content characteristics, and other user interactions [1][2]. The purpose of such systems is therefore not simply to determine which content exists on a platform but also to determine which content should receive greater visibility for a particular user [5].

Large-scale recommendation acts as an information filtering layer between an enormous content catalogue and the limited attention of individual users [5]. Research on YouTube's recommendation architecture demonstrates that large



recommendation systems can separate the process into candidate generation and ranking. Candidate generation identifies a smaller collection of potentially relevant videos from a much larger catalogue, while ranking models subsequently determine the order in which those candidates should be presented [1]. The influence of recommendation systems becomes particularly important because users do not always actively search for everything they watch. A recommended video can introduce a person to content, a creator, topic, or viewpoint that they were not previously looking for. If the user watches or interacts with that content, the interaction can become a new signal for future recommendations [1][2]. This creates a feedback loop in which previous behaviour influences future recommendations and future recommendations can influence subsequent behaviour.

For example, a user who watches several videos about Python programming may subsequently receive more programming-related recommendations. If the user continues watching those videos, the system receives additional evidence that programming content is relevant to that user. Such adaptive personalization is a fundamental characteristic of modern recommendation systems [1][2].

II. OBJECTIVES OF THE STUDY

The primary objective of this study is to explain the basic working principles of online video recommendation systems and to understand how these systems influence users' content discovery experiences. The study also aims to identify the major user and content signals that can influence video ranking, including viewing history, searches, likes, shares, follows, viewing duration, and content characteristics [1][2]. Another objective is to examine how personalized recommendations affect content discovery and viewing behaviour and to understand the relationship between recommendation, popularity, engagement, and content visibility [6][7]. The study further examines concerns associated with recommendation systems, including filter bubbles, algorithmic amplification, reduced content diversity, transparency, and user autonomy [3][4][8][9]. Finally, the study aims to identify important gaps in existing research and suggest possible directions for future investigation.

III. RESEARCH QUESTIONS

This study investigates several questions concerning the relationship between recommendation algorithms and online video consumption. The first question concerns the types of information that recommendation systems use to predict what an individual user may watch. The second question examines how viewing and interaction behaviours influence subsequent recommendations. The third question considers how personalization and ranking can change the range of content encountered by users. The fourth question examines the major benefits and limitations of recommendation-driven content discovery. The fifth question considers whether recommendation mechanisms can contribute to popularity concentration or reduced content diversity. Finally, the study considers what research gaps remain concerning the long term influence of recommendation algorithms on users' viewing habits.

IV. LITERATURE REVIEW

4.1 Recommendation Systems as Information Filters

Recommendation systems have become an important component of modern digital services because users are exposed to quantities of information that are significantly larger than they can reasonably consume. Recommender systems help address this information overload by selecting and ranking items that are predicted to be relevant to individual users [5]. The basic objective is to reduce the effort required to identify useful or interesting content from a large collection [5]. Recommendation systems can use several approaches. Collaborative filtering relies on patterns of interaction between users and items, while content-based recommendation considers characteristics of items and the interests previously demonstrated by a user. Modern recommender systems can combine multiple approaches and use machine learning techniques to generate personalized predictions [5]. The growth of recommendation technology has therefore changed the role of digital platforms. Instead of simply providing access to content, platforms increasingly organize the



order in which content is encountered. The recommendation system becomes part of the user's information environment and can influence which items receive attention [5].

4.2 How Video Recommendation Works

Research on YouTube provides an important example of how recommendation systems operate at large scale. Covington, Adams, and Sargin described a two-stage architecture involving candidate generation and ranking [1]. Candidate generation reduces a very large collection of possible videos to a smaller group of potentially relevant candidates. The ranking stage then evaluates those candidates and determines their relative order [1]. This architecture is important because a platform cannot efficiently perform complex ranking calculations over every available video for every user at every moment. Candidate generation makes the problem computationally manageable, while ranking allows the system to make more detailed predictions about which items should be presented first [1]. The result is that recommendation involves both selection and ordering. A video that is not selected during candidate generation may never appear in the user's immediate recommendation set, while videos that reach the ranking stage compete for limited user attention [1].

4.3 User Behaviour and Personalized Feeds

User behaviour is one of the most important sources of information used by personalized recommendation systems. Actions such as watching videos, liking content, commenting, sharing, following creators, searching for topics, and skipping videos can provide information about a user's interests [2]. These signals allow recommendation systems to continuously update their predictions [1][2]. TikTok's public explanation of its recommendation system identifies user interactions, content information, and user-related information as factors that can influence recommendations [2]. The platform also explains that different interactions can carry different levels of importance. For example, completing a video can provide stronger evidence of interest than simply encountering the video [2]. This demonstrates that recommendation systems do not necessarily treat all user actions equally. Repeated behaviour can provide stronger evidence about preferences, while individual interactions may have a smaller or temporary influence [1][2]. User behaviour can therefore be both an input and an outcome of recommendation. A user watches content because it was recommended, and that viewing behaviour may then influence what the system recommends next [1][2]. This relationship makes the recommendation process dynamic rather than static.

4.4 Engagement and Attention

Engagement is an important concept in recommendation systems because platforms need measurable signals to estimate whether users find content interesting or relevant. Signals may include clicks, watch time, completion, likes, comments, shares, and return behaviour [1][2]. However, engagement does not necessarily represent satisfaction. A user may watch a video because it is highly attention-grabbing without considering the experience valuable after the viewing session. Research has therefore questioned whether optimizing recommendation systems for immediate engagement necessarily produces outcomes that users themselves consider desirable [6]. Khambatta et al. examined recommendation systems in relation to users' actual preferences and their ideal preferences, highlighting the possibility that recommendations optimized around observed behaviour may not always correspond perfectly with what users ultimately consider beneficial or desirable [6]. This suggests that recommendation quality should not be evaluated solely through immediate engagement [6]. A recommendation system that successfully maximizes watch time may produce different outcomes from a system that attempts to maximize satisfaction, diversity, quality, or long-term value [6]. Consequently, the objective function used by a platform can influence the type of content that users encounter.

4.5 Popularity Bias and Content Visibility

Popularity can play an important role in determining content visibility. Videos that receive large numbers of views, likes, comments, and shares generate behavioural signals that may indicate relevance or interest. At the same time, recommendation can increase the exposure of these videos and create opportunities for additional engagement [7]. This creates a possible feedback process in which recommendation increases exposure, exposure generates engagement, engagement increases visibility, and increased visibility produces further exposure [7]. Research on recommender systems has demonstrated that recommendation mechanisms can affect the distribution of attention across items and



can contribute to popularity-related effects [7]. Popularity bias does not necessarily mean that recommendation systems intentionally favour established creators or that popular content is of lower quality. Instead, it indicates that existing popularity and algorithmic visibility can interact in ways that influence which content receives attention [7]. For less-known creators, this can create a challenge because they may have fewer initial engagement signals. If a system strongly relies on historical engagement, content with limited previous exposure may have fewer opportunities to enter highly visible recommendation positions [7].

4.6 Filter Bubbles and Content Diversity

The possibility of filter bubbles is one of the most widely discussed concerns associated with personalized recommendation. A filter bubble refers to a situation in which personalization may limit the range of information encountered by an individual because the system repeatedly presents content that is similar to the user's previous interests [8]. For example, a user who repeatedly watches videos about a particular political viewpoint, entertainment genre, or subject may receive more content related to that topic. Such personalization can make the feed more relevant, but it may also reduce exposure to unfamiliar topics [8][9]. However, the evidence concerning filter bubbles is not straightforward. Users themselves actively select content, and these choices can contribute substantially to the information they encounter [3]. Robertson et al. found that users chose to engage with more partisan news than they were exposed to through Google Search, demonstrating that consumption patterns cannot necessarily be attributed entirely to algorithmic ranking [3]. Research on online consumption also indicates that algorithmic curation can have different effects depending on the platform, content category, user population, and definition of diversity [9]. Therefore, the existence and strength of filter bubble effects should be examined through empirical research rather than treated as an inevitable consequence of personalization.

4.7 Algorithmic Amplification

Recommendation systems can also influence the visibility of particular categories of content. Research examining recommender systems has identified cases in which ranking mechanisms can produce unequal exposure across communities and content types [4]. Amplification becomes especially relevant when engagement signals are important components of ranking. Content that generates strong emotional reactions may receive substantial interaction, and these interactions can potentially increase its visibility [4]. However, algorithmic amplification should not automatically be interpreted as deliberate promotion. An algorithm can increase the visibility of particular content because the content performs strongly according to the model's ranking criteria without the system being explicitly designed to promote that content [4]. Independent auditing is therefore important for understanding what types of content are amplified, under which conditions amplification occurs, and whether amplification is consistent across different users and contexts [4].

V. RESEARCH METHODOLOGY

This study adopts a narrative literature review methodology to examine how recommendation algorithms influence online video consumption. The review draws primarily on academic research concerning recommender system architecture, personalization, user behaviour, algorithmic curation, popularity bias, content diversity, and algorithmic amplification. Selected first party platform documentation is also considered to understand how platforms publicly describe their recommendation mechanisms [1][2].

Academic publications are given greater importance when discussing observed effects and research findings, while platform documentation is used mainly to explain publicly disclosed recommendation factors. This distinction is necessary because a platform's explanation of its recommendation process describes the mechanisms or signals it acknowledges but does not independently establish the magnitude or causal effect of those mechanisms.

The literature is analysed thematically rather than statistically. The reviewed studies differ in platform, population, research design, variables, and outcome measures. Because of these differences, combining their numerical findings into a single effect estimate would not be methodologically appropriate. Instead, this study compares the mechanisms and patterns identified across different studies and considers where existing findings agree, differ, or remain uncertain.



The methodology therefore provides a conceptual understanding of the relationship between recommendation systems and online video consumption rather than attempting to calculate a new statistical effect size.

VI. RESULTS

The literature reviewed in this study indicates that recommendation algorithms influence online video consumption through a combination of personalization, ranking, behavioural signals, popularity, and feedback mechanisms [1][2][7]. The influence does not result from a single universal algorithm or a single signal. Different platforms use different models, features, objectives, and ranking strategies [1][2]. One important finding is that recommendation changes the starting point of viewing. Without personalized recommendation, users would have to search through large catalogues manually or depend primarily on direct searches and subscriptions. Recommendation systems instead place selected videos directly in front of users, reducing the effort required to discover content [1][5]. A second finding is that recommendation is adaptive. User behaviour is repeatedly incorporated into the recommendation process [1][2]. Consequently, two individuals using the same platform may receive very different feeds because their previous behaviour differs. The same individual may also receive different recommendations over time as their interests and interactions change [1][2].

A third finding is that ranking affects attention. A platform may have thousands or millions of potentially relevant videos, but users generally view only a small number of them. Therefore, the position and visibility assigned to a video can affect the probability that the user will notice and watch it [1]. Recommendation systems can consequently be understood partly as systems for allocating limited user attention. A fourth finding is that recommendation and user behaviour influence each other. Users influence recommendations through their searches, viewing patterns, likes, shares, follows, and other interactions [1][2]. At the same time, recommendations influence which content becomes easily visible to users. The resulting viewing pattern is therefore produced through a continuous interaction between human behaviour and algorithmic ranking [3][9]. A fifth finding concerns popularity. Popular content can receive additional visibility because it generates strong engagement signals, while recommendation itself can generate further exposure and engagement. This creates conditions under which already visible content may continue to receive substantial attention [7].

VII. DISCUSSION

The findings indicate that recommendation algorithms play a meaningful role in shaping the environment in which online viewing decisions take place [1][5]. However, algorithmic influence should not be confused with complete control over user behaviour. Users remain capable of actively searching for specific content, ignoring recommendations, following particular creators, using external links, changing available settings, or leaving a platform. One of the major advantages of recommendation systems is improved discoverability. Online platforms contain more content than users can reasonably examine. Personalized ranking reduces the effort required to locate relevant material and can help users discover educational resources, entertainment, music, news, niche subjects, and new creators [1][5]. Another important benefit is adaptability. Recommendation systems can respond to changing interests instead of assuming that a user has one permanent preference profile [1][2]. A user may temporarily become interested in programming, travel, cooking, fitness, gaming, or another subject, and changes in viewing behaviour can lead to corresponding changes in recommendations.

At the same time, personalization can reinforce existing patterns. When recommendation systems rely strongly on similarity and engagement, users may repeatedly encounter content that resembles what they have already watched. This can improve short-term relevance but may reduce certain forms of unexpected or diverse discovery [8][9]. The relationship between recommendation and popularity is also significant. Content that receives high engagement can potentially obtain additional exposure, while additional exposure can generate more engagement. Such feedback can concentrate attention around already successful content [7]. The evidence concerning political and social consequences requires particular caution. Some studies have identified algorithmic amplification or differences between



algorithmically curated content and user-selected content [3][4][10]. Other research indicates that users' own preferences and choices contribute significantly to their consumption patterns [3]. Therefore, recommendation should be understood as one component of a broader socio-technical system involving users, creators, platform policies, social networks, and ranking algorithms.

Transparency is another major issue. Users may understand that their feed is personalized without knowing precisely why a particular video has been recommended or why it appears above another video. Platforms may describe general categories of signals while not publicly disclosing complete ranking models, feature weights, training datasets, or model parameters [1][2]. This creates a difference between general awareness of personalization and detailed understanding of individual recommendations. Finally, the objectives used to optimize a recommendation system are important. A system primarily optimized for immediate engagement may favour content that produces rapid interaction, whereas a system that also considers satisfaction, diversity, quality, and long-term user value could generate different recommendations [6]. Recommendation evaluation should therefore be treated as a multi-objective problem rather than being reduced to a single engagement metric.

VIII. LIMITATIONS OF THE STUDY

This study has several limitations. First, it uses a narrative literature review rather than a systematic meta-analysis, meaning that it does not provide a statistically combined estimate of the effects reported across different studies. Second, commercial recommendation algorithms are largely proprietary and can change frequently, making it difficult for researchers to determine the complete ranking process from publicly available information [1][2]. Third, different platforms use different algorithms, objectives, and content environments, meaning that findings from one platform cannot automatically be generalized to all online video services. Fourth, user behaviour and algorithmic influence are difficult to separate because users and recommendation systems continuously affect one another [3][9]. Fifth, some of the literature examined in this study focuses on political or social information rather than entertainment video, and these findings should therefore be interpreted within their original context. Finally, this study does not conduct a new controlled user experiment and therefore does not estimate a new causal effect size for recommendation algorithms.

IX. FUTURE SCOPE

Future research should move beyond simple measures such as clicks, views, and watch time. Controlled experiments could compare personalized feeds with alternative ranking strategies and measure not only engagement but also user satisfaction, content diversity, discovery of new creators, perceived control, and long-term viewing outcomes. Research has already highlighted the distinction between immediate engagement and users' ideal preferences, suggesting that future recommendation studies should consider broader measures of user welfare [6]. Longitudinal research represents another important direction. Short-term experiments can demonstrate immediate changes in recommendations, but longer studies are necessary to understand whether repeated exposure to personalized content changes users' interests, preferences, or viewing habits over weeks and months [8][9]. Independent auditing should also receive greater attention. Because commercial recommendation systems are generally proprietary, external researchers need methods for evaluating observable recommendations without requiring access to the complete internal model. Auditing research has already demonstrated the usefulness of examining recommendation outputs to identify possible amplification patterns [4].

Research in India would be particularly valuable because much of the existing literature has focused on platforms and populations outside the Indian context. Language, culture, mobile device usage, internet access, data costs, regional content, and creator ecosystems can influence how users interact with recommendation systems. Future studies could therefore examine recommendation effects among Indian users and compare English language content with Hindi, Marathi, and other regional language content. The increasing use of artificial intelligence also creates new research opportunities. Modern recommendation systems increasingly rely on advanced machine learning models and large-



scale behavioural data [1][5]. Future research can investigate how these technologies influence personalization, content diversity, user autonomy, and transparency.

X. CONCLUSION

Recommendation algorithms have become a central mechanism through which people discover and consume online video [1][5]. They reduce the difficulty of navigating enormous content catalogues by predicting which items may be relevant to an individual user and ranking a smaller collection of candidates for attention [1]. These predictions can incorporate viewing history, searches, interactions, content characteristics, popularity, and other behavioural signals [1][2]. The literature reviewed in this study indicates that recommendation systems can make online video discovery more convenient, relevant, and personalized [1][5]. At the same time, recommendation mechanisms can create feedback loops in which exposure influences behaviour and behaviour subsequently influences future exposure [1][2]. Popularity and engagement can reinforce visibility [7], while highly personalized ranking may reduce some forms of content diversity [8][9]. However, the evidence does not support the idea that algorithms completely determine what people watch. Human preferences, active searches, social relationships, creators, platform design, and recommendation systems interact continuously [3][9]. Users influence algorithms through their behaviour, while algorithms influence users by shaping the content environment in which choices are made.

The most useful way to understand recommendation algorithms is therefore to view them as systems that shape the choice environment rather than completely determine individual behaviour. Their influence is significant because they determine which items become more visible, which content is easier to discover, and which viewing choices are repeatedly presented [1][5]. Future research should evaluate recommendation systems using multiple measures, including engagement, satisfaction, diversity, quality, transparency, user autonomy, and long-term outcomes [6]. Greater transparency and independent auditing can help researchers and users better understand how personalized feeds operate [4]. Ultimately, the important question is no longer only what content exists online. It is also which content becomes visible to each individual, in what order, and why.

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