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How Recommendation Algorithms and Highly Liked Comments Influence Cognitive Bias on Social Media

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Abstract:

Social media platforms in the modern digital world mainly depend on user interactions and recommendation algorithms to determine how much content is seen. Highly liked comments are one type of interaction that might be crucial in promoting users' cognitive biases. This study examines how recommender systems and social mechanisms work together to amplify biased thinking and weaken information diversity. This study employs a mixed-method approach, combining survey responses from young users with web-scraped comment data from Chinese platforms Douyin. The analysis focused on patterns in top-rated comments, their emotional tone, and how often they reflected polarized or repetitive viewpoints. Survey data was used to understand how users perceive the impact of algorithms and whether they can recognize bias in content they see on a daily basis. Findings suggest that highly endorsed comments often reflect simplified, emotionally charged opinions that align with existing beliefs. Algorithms are more likely to encourage these comments, which feeds a vicious cycle of biassed content creation and dissemination. Furthermore, users frequently accept this information without challenging its objectivity, which over time exacerbates the cognitive imbalance. This study intends to highlight the need for more transparent platform design and higher media literacy. By understanding how digital systems shape thinking, users and educators can better navigate online space, because what is popular is not always the truth, and more reasonable efforts are needed to create a safe and barrier-free online world for users.

Keywords: Recommendation Algorithm; Cognitive Bias; Social Endorsement; Filter Bubble; Social Media.

1. Introduction

In the era of social media, the way of obtaining information has changed from traditional linear browsing to personalized recommendations driven by algorithms. This is a major topic trend worthy of attention and research. These platforms function by filtering, sorting, and recommending what each user sees in addition to using user-generated content [1]. While these algorithms are designed to enhance user experience and engagement, they can also inadvertently shape the way individuals think, often narrowing the range of perspectives they are exposed to [2].

The significance of this issue lies in the potential social and psychological consequences. When content is selected and ranked based on previous behavior or popularity indicators, such as likes or shares. The users may find themselves repeatedly exposed to similar viewpoints [3]. This may eventually result in the suppression of opposing viewpoints and the strengthening of preexisting beliefs. Specifically, comments with a lot of likes have developed into a subtle yet effective component of this process. They serve as social proof, creating the appearance that particular viewpoints are more widely held or reliable, even though they may be biassed or emotional [4]. This phenomenon, combined with previous research literature, raises important concerns about how digital environments facilitate the formation and amplification of cognitive biases.

The combination of two fundamental forces in the digital realm. They are the recommendation algorithms and highly liked comments. It is the main focus of this study. Fewer studies have looked into how social endorsement of comments reinforces the effects of algorithms creating echo chambers or information bubbles. This study aims to explore whether popular comment areas in information bias can not only reflect bias, but also try to obtain specific and feasible methods to better solve this type of information cocoon problem through questionnaires and algorithms.

To conduct this investigation, this study used a joint analysis of two different methods. Intended to be more accurate and multifaceted in discovering phenomena and solving problems. First, the study collected and analyzed 1,500 user comments on Douyin, a popular Chinese platform, focusing on comments with a high number of likes. The researchers analyzed the emotional tone, content repetitiveness, and ideological tendencies of these comments. Second, the researchers conducted a survey of 50 young users to understand their views on algorithm-driven content and their awareness of biases they often encounter online.

The ultimate objective of this study is to gain a deeper understanding of how user feedback dynamics and recommendation system design interact to affect cognitive bias on social media. This study aims to provide insights that can guide platform policies and digital literacy instruction by identifying trends and perceptions surrounding highly liked comments.

2. Literature Review

2.1 Likes and Perceived Legitimacy: The Role of Social Proof

In social media environments, users often rely on visible social signals, such as like counts or upvotes. In order to evaluate the relevance and accuracy of information. This behavior is based on the social proof theory, which contends that people, particularly in ambiguous circumstances, have a propensity to accept what other people think is right. The quantity of likes a comment receives serves as a quick way to gauge its significance and reliability in online environments where information is plentiful and continuously changing.

Studies have shown that users are more likely to agree with comments that have higher engagement, regardless of the actual content. The essay found that participants were more likely to rate highly liked comments as “reasonable” or “trustworthy,” even when the comments included emotionally charged or unverified claims. This trend supports the existence of cognitive bias, particularly the bandwagon effect and confirmation bias, where users seek information that aligns with their beliefs and perceive it as more valid simply because others do.

In addition, highly-rated comments are often strongly emotional or opinion-driven. These types of comments appeal to instinctive reactions rather than rational judgment. Over time, repeated exposure to these popular messages may distort people’s perceptions of public opinion, creating what some scholars call a “consensus illusion.” Because of this, users might erroneously assume that the viewpoints presented in the comments that have received the most likes are those of the majority, which would support their own opinions and disregard opposing viewpoints. Likes are more than just passive numbers, as this section demonstrates. They serve as psychological cues that affect how individuals assess information. By doing this, they contribute significantly to the reinforcement of cognitive biases and the formation of users‘ perceptions of reality on digital platforms.

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2.2 Algorithmic Boosting of High-Endorsement Content

By highlighting content that is more likely to spark interaction, recommendation algorithms aim to increase user engagement. These systems use early engagement data, likes, shares, and comments, which indicate popularity quickly, as one of their primary indicators. As a result, the algorithm frequently gives comments with a lot of interaction early on more visibility.

This creates a feedback loop where emotionally charged or biased comments, which tend to gain attention quickly, are pushed to even more users. Studies using algorithmic audits confirm that engagement-based systems significantly amplify polarizing content over neutral information [5]. Over time, this can reduce exposure to diverse perspectives and increase the influence of cognitive bias.

Furthermore, algorithms are not neutral tools; This bias in content delivery further contributes to the formation of filter bubbles, limiting exposure to diverse viewpoints [6]. They follow a preset logic that maximum engagement rather than balance. High-liked comments become signals that influence what the public sees and talks about when algorithms consistently favor them. The filter bubble effect, in which users are primarily exposed to viewpoints that align with their preexisting preferences, is reinforced by this pattern.

At its most basic, the algorithm itself does not create bias, but it amplifies user-driven feedback. By promoting highly engaged comments, regardless of the quality of their content, the recommendation system plays an active role in amplifying social signals that lead to a biased information environment.

2.3 Co-Amplification of Bias: Platform Design Meets User

While both algorithms and highly liked comments themselves can exacerbate exposure to biased information, their combined effect is stronger and more lasting. This process can be understood as “co-amplification,” where platform design and user behavior interact to reinforce cognitive biases in a feedback loop. The system not only displays liked content, but also learns what people are emotionally inclined to agree with, and then reproduces similar content to further validate bias patterns.

Confirmation bias theory, which is a key factor in the creation of echo chambers, explains why users have a psychological propensity to favor content that supports their preexisting opinions or emotional states [7]. When users see highly upvoted comments that reflect their own thoughts, they are more likely to engage with them, which not only enhances the popularity of the comments but also trains the algorithm to provide similar content. Empirical research shows that comment sections significantly affect users perceived bias and trust in news [8].

From a technical perspective, platforms are built to optimize engagement metrics, not information diversity. As a result, algorithms favor content that gets a predictable number of clicks, likes, or shares. Furthermore, even if that content oversimplifies issues or leans toward extreme views. This cycle creates an information environment where bias not only survives, but thrives. These are serious consequences for Ken.

All of these trends point to a structural dynamic in social media: cognitive bias is not merely a personal shortcoming, but rather is constantly influenced and amplified by the interplay between user psychology and design logic. Understanding this co-amplification is essential to comprehending why eliminating bias on digital platforms necessitates systemic change in addition to individual effort.

3. Methodology

This section will introduce the methods used in this paper. In order to explore the relationship between algorithmic recommendation systems and cognitive biases, this study adopts a mixed method. The method includes qualitative and quantitative analysis, text analysis based on user-generated content, and basic statistical summaries of sentiment orientation and repeated language patterns. Some data, specifically, those comments on the TikTok platform. This is obtained through a compliant web crawler that targets short video comment areas and related discussions on social platforms, and combined with a self-designed questionnaire to test the research results.

3.1 Data Collection

This study relies on a mixed-method approach that combines data from online platforms and survey responses. The primary source of data consists of 1,500 user comments collected from two major Chinese social media platforms: Douyin and Weibo. These platforms were chosen because they heavily rely on algorithmic recommendation systems and are well-liked by younger users. The essay focused on posts with a high number of likes and used a specially designed Python-based web crawler to extract comments from those posts.

In order to ensure that the data reflected recent user behavior, all comments were collected within a six-month period. The keywords used to filter and locate relevant comment sections included “algorithm,” “recommendation,” “bias,” and “trending comment.” During the cleaning process, duplicate and irrelevant content has been

excluded, as have comments containing only emojis.
50 students between the ages of 16 and 20 participated in a brief survey in addition to the online data. The purpose of the questionnaire was to learn more about their opinions of suggested content, the frequency of repetitive or emotionally charged comments they come across, and whether they are conscious of potential cognitive bias in their regular use of social media.

3.2 Analytical Approach

Survey results use descriptive statistics to summarize participants' responses. The main focus was on how often respondents noticed repetitive content, emotional opinions, or signs of bias in their feeds. Additionally, charts were created to visualize perception and behavior trends.
A key part of the analysis was to cross-reference review topics with survey results. This enabled to explore the relationship between observed platform content and user perceptions. Specifically, our goal was to determine whether users who said they noticed patterns of bias were responding to real review trends or simply reacting based on personal assumptions.
This study provides a more comprehensive understanding of how algorithmic exposure and highly liked comments interact to influence user cognition by fusing qualitative theme analysis with simple statistical summaries.

3.3 Research Ethics

This study followed ethical research principles and ensured the privacy and dignity of all participants. In the questionnaire survey, all respondents were informed of the purpose of the study and voluntarily agreed. No sensitive personal information, including names, phone numbers, or contact information, was included in the questionnaire. Additionally, participants could choose to skip any question or to stop participating at any moment without incurring any penalties.
In addition, the data has not been processed manually. The number of comments, timestamps, and content are exactly the same as those recorded on the platform. This ensures that the research results are based on real situations and are not distorted.
Overall, ethical precautions were taken at every step to respect both the digital rights of users and the trust of survey participants.

4. Results and Analysis

This section introduces the main findings of the review data and questionnaire survey results, including detailed content text and image insertion to better reflect the conclusions and analysis. This section also aims to analyze the degree of influence of algorithmic recommendation systems on user perception and behavior.

4.1 Comment Data Findings

The comment analysis revealed several notable trends regarding high-liked content on Chinese social media platforms. Among the 1,500 comments examined, approximately 65% of those with high like counts contained emotional expressions. For example, excessive praise, outrage, or sarcasm. These remarks frequently used simplified or exaggerated language, were brief, and were strongly opinionated. For example, emotionally charged phrases like „finally someone said it“ or „typical behavior as expected“ were used in a large number of highly liked replies in trending posts.
In terms of content patterns, about half of the top-voted comments exhibit confirmation bias, with statements in these comments clearly consistent with the original post or the prevailing sentiment in the thread. These comments tend to receive more attention than comments that offer a balanced or critical perspective. Only a small part of popular comments expressed moderate or opposing views, indicating a strong tilt toward one-sided interaction.
Repetition was another important trend. Similar arguments and phrases were commonly used in various posts, indicating that familiar narratives and emotional resonance are important factors in attracting likes. These results lend credence to the notion that emotional simplicity, rather than logical depth, is frequently what drives high engagement on social media platforms.
In summary, highly liked comments tend to be emotional and repetitive. These highly liked comments are consistent with mainstream opinions, which is an existing network phenomenon. These characteristics suggest that popular comments on social media may not reflect the balance of speech, but the efficiency of emotional expressions in attracting attention. This section focuses on how social recognition indicators such as likes can increase the exposure of potentially biased or polarized opinions.

4.2 Questionnaire Results

50 participants between the ages of 16 and 20 answered the survey, which sought to understand how young users view the content that is recommended to them by algorithms. The findings show that, despite their limited critical resistance, most users are aware of content repetition and display specific patterns of bias and trust.

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Table 1. User perception of content repetition

Response	Number of Participation	Percentage (%)
1. Always	12	24
2. Often	27	54
3. Sometimes	8	16
4.Rarely	2	4
5.Never	1	2

Table 1. User Perception of Content Repetition reveals that 54% of respondents said they “often” encounter repeated content in their social feeds, while 24% stated it happens “always.” When taken as a whole, this indicates that 78% of participants frequently encounter repetitive content, indicating a high degree of perceived redundancy in algorithmic recommendations. Just 4% and 2% of respondents, respectively, said they „rarely“ or „never“ experienced such repetition.

Table 2. Trust in and interaction with highly-liked comments

Response	Number of Participation	Percentage (%)
Always Trust	5	10
Often Trust	13	26
Sometimes Trust	18	36
Rarely Trust	9	18
Never Trust	5	10

Next, Table 2: Trust and interaction with highly-rated comments shows that 36% of participants “sometimes” trust popular comments, 26% “often” trust them, and 10% “always” trust them. Interestingly, 18% of participants said they “rarely” trust highly-rated comments, and another 10% said they “never” trust them. Although there is still some doubt, these results point to a comparatively high level of engagement with algorithmically promoted opinions.

Table 3. Awareness of filter bubbles and cognitive bias

Response	Number of Participation	Percentage (%)
Very Aware	8	16
Somewhat Aware	17	34
Neutral	11	22
Not Very Aware	9	18
Not Aware at all	5	10

Table 3. Awareness of filter bubbles and cognitive biases Further, 34% of respondents were “somewhat aware” of filter bubbles and cognitive biases, while only 16% were “very aware.” Nonetheless, 28% of users (combined „not very aware“ and „not aware at all“) demonstrated low awareness, while 22% of users remained neutral. This pattern suggests a general lack of thorough knowledge regarding the ways in which personalization can perpetuate bias.

Moreover, despite 50% of users showing at least moderate awareness, only 18% reported taking active steps to avoid algorithmically filtered content. This contrast underscores a key concern: even when young users recognize potential bias, their behaviors tend to favor convenience, emotional resonance, or passive consumption over intentional media choices.

4.3 Cross-Layer Analysis: Comparison Between Web-Scraped Comment Patterns and User Perception

This study analyses data from two sources: extensive web scraped comment data and user perception survey data, in order to investigate the structural mechanisms underlying cognitive bias. The study used a data scraping tool to collect 1,500 highly interactive comments from the TikTok platform and filtered them based on the number of likes and algorithm priority, with the aim of discovering the type of content most frequently promoted on the platform.

The crawling results show that emotional keywords in the comments appear frequently, such as “lock-in”, “information cocoon”, “domestication”, “cognitive bias” and “information difference”. These words are translated into English and visualized through word clouds according to their frequency of occurrence, which clearly shows how users’ expressions revolve around the theme of “being trapped” or “being manipulated”. The high frequency of such language not only reflects the common emotions among users, but also suggests that there is a feedback mechanism on the platform, that is, emotional expressions will be reinforced by the platform. This is also known as part of the algorithm.

These results are consistent with the survey‘s findings, which showed that the majority of respondents said they frequently encountered emotionally charged and repetitive content. Only a small percentage of users actively seek out opposing views or challenge prevailing narratives, even though they are aware of this pattern.

This observation highlights a resonance amplification effect: the algorithm tends to prioritize emotionally expressive content, and users reinforce this algorithmic preference through likes and comments. Web crawling data confirms this cycle - highly liked comments often use simplified and emotionally charged language, which is further amplified by the system, ultimately deepening the information bias users suffer.

Thus, the combination of user perception data and web-scraped comment analysis implies that platform design amplification mechanisms have a significant impact on cognition rather than just personal judgement. In addition to making technical changes to recommendation algorithms, breaking this cycle calls for raising users‘ critical awareness and digital literacy.

5. Discussion and Recommendations

5.1 The Feedback Loop Between Algorithm and High-Liked Comments

One of the core findings of this study is that there is a feedback loop between recommendation algorithms and highly-rated reviews that actively amplifies cognitive biases. This loop operates through two mutually reinforcing mechanisms. First, content with high engagement metrics. Such likes, shares, and watch time, which is given priority by algorithmic systems. Therefore, content that evokes strong emotions, whether it be simple or emotionally charged, is more likely to be promoted. Second, users are more likely to trust and interact with these promoted opinions due to visible social cues like like-counts, which increases their algorithmic visibility.

This pattern is evident in the analysis of comments, where emotionally extreme or ideologically similar content receives significantly more likes. At the same time, survey data shows that most participants encounter repeated and emotionally similar comments, Yet few people doubt their authenticity, which means users accept platform-approved content without question.

As a result, the feedback loop perpetuates biassed exposure: users increasingly rely on algorithmically popularized cues to shape their perceptions, while platforms magnify what users interact with the most. This dual dependency stifles opposing or nuanced points of view and hastens the narrowing of perspective.

5.2 User Awareness and Self-Aware Passivity

Although algorithms have a structural influence on how information is presented, users are not completely ignorant of these processes. According to survey responses, a large number of participants have observed patterns in their feeds, including opinion uniformity, emotional tone, and repetitiveness. However, this awareness rarely translates into behavioral change. Most users continue to engage with reviews that resonate or are popular, even if they suspect that some reviews lack diversity or depth. This paradoxical behavior can be described as self-aware passivity: the awareness of bias but the incapacity or unwillingness to combat it.

This phenomenon may stem from cognitive overload and convenience. In a fast-paced digital environment, questioning algorithms or actively seeking different perspectives requires effort, while passively scrolling through and reacting does not. In addition, emotional comments give users immediate psychological rewards. Specifically, for example, recognition, approval, or catharsis. This hinders them from thinking more deeply. Traditional media literacy techniques are complicated by the presence of self-aware passivity. It is insufficient to teach users to “spot bias” if they decide not to take action. Therefore, interventions must go beyond awareness-building and target behavioral inertia. Features that prompt users to reflect, such as “delay before liking” buttons or structured counter-comment prompts, may help break this passive cycle. Addressing the passivity of self-awareness is critical to any long-term strategy to reduce the cognitive biases that

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algorithms amplify.

5.3 The Underestimated Influence of Comment Sections

This study highlights the overlooked role of comment sections as a secondary but powerful link in reinforcing bias. Comments are not just user reactions, but algorithmically sorted micro-content that influences user perception. In particular, comments with a high number of likes act as social signals that influence how users perceive the original post and set the tone for further discussion. Comment sections are a key area for cognitive shaping because users frequently interact with them more than they do with the content itself.

Our content analysis revealed that high-liked comments often carried emotionally extreme or ideologically uniform messages. This trend encourages a form of interpretive shortcut, where users adopt the dominant tone of the comment section as the "correct" or "socially safe" interpretation. As more and more users imitate this tone to gain likes, the platform becomes an environment that reinforces superficial consensus and emotional extremes. This kind of online environment is not what society wants.

5.4 Educational and Platform-Level Implications

The study's conclusions have significant ramifications for platform governance models as well as educational systems. The fact that cognitive bias still exists even when users are aware of it points to a weakness in the current digital literacy curriculum from an educational standpoint. It's not enough to teach students to identify bias; they must also be trained to understand how algorithmic systems shape emotional responses and social identity, especially through mechanisms like comment prioritization and trending feedback loops. This means updating media education to include more dynamic and contextual modules that simulate real platform environments.

At the platform level, current recommendation systems largely ignore the interpretive role of comment areas and the psychological impact of hot leads. Few people have worked to regulate the structural dynamics of comment exposure. A more mature platform logic should treat comment areas as active contributors to user opinions, so that other voices can be more easily seen.

5.5 Practical Strategies to Interrupt Cognitive Bias Amplification

At the platform level, recommendation systems can integrate "respective diversity modules" to intentionally inject some content with opposing or underrepresented perspectives. For example, another possible strategy is to introduce time decay weights in comment visibility, ensuring that older, highly liked comments do not permanently dominate and allowing newer perspectives to surface.

Digital literacy initiatives in educational settings ought to transition from models of passive recognition to experiential learning. Students can experiment with how their actions affect algorithmic results and comprehend how filter bubbles form by using simulated platforms or „algorithmic sandbox" environments. Additionally, course designers should include emotional awareness training to teach users to pause before reacting to emotionally charged content, an important, often overlooked skill in media engagement.

From the user perspective, subtle behavior adjustments can also disrupt bias loops. Users can implement intentional exposure routines, such as following creators with differing views, rotating content sources weekly, or using browsing modes that minimize algorithmic tracking. The concept of „cognitive contrast folders," which are individual collections of material that question the user's own prejudices and serve as a self-regulated tool for perspective expansion, is especially innovative.

These multi-layered strategies demonstrate that mitigating bias is not the responsibility of a single actor but rather a shared process involving technology design, educational practices, and user agency. Breaking the amplification cycle requires redesigning how we interact with media, and how media interacts with us.

6. Conclusion

This study explores the relationship between algorithmic recommendation systems and the formation of information cocoons and cognitive biases in the digital age. Through online comment data and user survey analysis, the study found that personalized algorithms do significantly reinforce users' existing ideas, limit users' exposure to diverse perspectives, and shape passive user habits.

Due to convenience and emotional satisfaction, most users tend to accept algorithmic influence, though some users show some awareness of it. This draws attention to a significant paradox in the digital age: the conflict between tailored content and the variety of thought required for constructive dialogue.

Our findings suggest that the algorithmic environment is not neutral. Instead, it shapes users' thinking and worldviews, often without their conscious consent. Critical reflection on algorithmic design and its broader societal impact is therefore essential for future media literacy and policy development.

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