

The Impact of YouTube Recommendation Algorithms on Filter Bubble and Media Bias

An Experimental Comparative Analysis Focused on Political Issues,
Environmental Issues, and Random Interests

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1. Research Topic

With the advent of the digital age, online video platforms like YouTube have become indispensable media for everyday content consumption. YouTube enhances user convenience and satisfaction by recommending personalized content based on users' interests and viewing history. However, as personalized recommendation systems advance, users increasingly encounter only those topics and viewpoints they already prefer, a phenomenon known as the "filter bubble." This tendency promotes information bias and confirmation bias, thereby restricting informational diversity.

In particular, the filter bubble phenomenon is a more serious issue in socially sensitive topics such as political issues or environmental concerns. Supplying information focused on specific interests can block users from encountering diverse perspectives or opposing viewpoints, thus further intensifying social conflicts and polarization. Against this backdrop, this study aims to empirically analyze how YouTube's recommendation algorithm forms filter bubbles and media bias according to users' specific interests—namely, political issues, environmental issues, and random interests.

Through this research, the biased nature of YouTube's recommendation algorithm will be objectively identified, and, based on these findings, ways to improve the algorithm to provide users with more balanced information will be explored. This study is expected to contribute to securing information fairness in the digital media environment and to enhancing users' media literacy.

2. Research Background

In recent years, social concerns and debates have grown about how online media and social media platforms, particularly YouTube's algorithmic recommendations, contribute to political polarization and the spread of misinformation. The influence of personalized information in shaping public opinion is expanding, especially in

topics such as environmental issues and political controversies, making empirical research on these phenomena increasingly urgent.

3. Research Questions

How does YouTube's recommendation algorithm form content bias according to users' interest topics (political issues, environmental issues, random interests)?

What are the differences in content diversity and information balance between users focused on political and environmental issues, and those with random interests?

4. Research Subject and Period

The research subject is the recommendation algorithm of the YouTube platform. Specifically, three types of user accounts were set up, each focused on political issues, environmental issues, and random interests. Data was collected by running the experiment for about two weeks, from March 15 to March 27, 2025, for each account.

5. Research Methodology

This study employs an experimental research methodology. Three types of user accounts were set up on the YouTube platform, with each account assigned specific content viewing patterns over a set period. The first account focused on political issues, the second account viewed content related to environmental topics, and the third account watched various subjects at random. Following the viewing activities, the types, frequency, and bias of the recommended content by YouTube were systematically analyzed for each account to evaluate the degree of filter bubble formation and content recommendation bias. Both quantitative analysis and qualitative content analysis were utilized, and the results will be presented through comparative analysis.

6. Expected Results

Through this research, it is anticipated that YouTube’s recommendation algorithm forms distinct filter bubbles according to users’ areas of interest, and the bias of recommended content will be closely related to those interests. In particular, for users with focused interests in political or environmental issues, there is a high likelihood that similar types of content will be repeatedly recommended, limiting content diversity. Conversely, for users with random interests, the filter bubble effect is expected to be relatively weak, with a broader variety of content recommended. These results are expected to highlight the need for improvements to YouTube’s algorithm and to emphasize the importance of developing strategies to enhance the diversity of users’ access to information.

7. Data Collection

To empirically analyze the degree of filter bubble formation and bias created by YouTube’s recommendation algorithm, this study established three separate accounts (Account_A, Account_B, Account_C), each representing a specific set of interests: political issues, environmental issues, and random interests. For each account, topic-specific interest content was defined in advance, and between March 15 and March 27, 2025, viewing activities were carried out to track and record the content recommended by the algorithm.

7.1 Interest Topic and Viewing Strategies for Each Account

| Account | Topic | Contents | Viewing Strategy |
|-----------|----------------------|--------------------------------------------------|----------------------------------------------------------------|
| Account_A | Political Issues | Trump/Biden speeches, U.S. political news, etc. | Focused viewing of political videos; analyze home feed changes |
| Account_B | Environmental Issues | Climate change, global warming, renewable energy | Watched documentaries and news on environmental topics; |

| | | | |
|-----------|---------------------------------|------------------------------------------------------------------|---------------------------------------------------------------------------|
| | | | record changes in recommended content |
| Account_C | Random Interests (proportional) | World news (2), pop music (3), cooking (2), soccer (2), cats (1) | Watched various topics according to set ratio; measure algorithm response |

7.2 Data Collection Procedures

1. Initial Account Setup

All accounts began with no prior search or viewing history. Immediately after creation, a screenshot of the default recommended videos (before viewing any content) was taken.

2. Viewing Activity Based on Interest Topics

Each account watched content according to its pre-assigned interest topic. For example, Account_A focused on watching Trump, Biden, and U.S. political videos; Account_B concentrated on environmental documentaries and news; Account_C viewed a variety of topics in set proportions (world news 2, pop music 3, cooking 2, soccer 2, cats 1) to systematically observe the algorithm's response to diverse interests.

3. YouTube Homepage Capture and Content Classification

After each day of viewing, a screenshot of the entire recommended content on the YouTube home page was captured and saved by date. From these images, all recommended videos were collected, recording each video's title, topic, channel, format (shorts/regular), and whether they showed political or other bias.

4. Content Classification Criteria

Recommended videos were analyzed according to the following criteria:

Topic classification: politics, environment, music, cooking, sports, animals, entertainment/variety, other

Type classification: news/current affairs, documentary, talk show, information/practical, shorts, humor, etc.

Political/environmental/other bias: whether a clear political stance or environmental message was present

5. Summary of Changes

After a set interval following topic-specific viewing, the recommended videos were summarized in terms of shifts in content proportions, topic bias, and persistence of relevance to the original viewing interest.

6. Analytical Tools

Collected image data was processed using OCR (Optical Character Recognition) to extract text and manually verified. The data was organized in Excel-based classification and analysis tables, enabling statistical visualization and comparative analysis.

8. Data Analysis

This section compares and analyzes the recommendation algorithm's filter bubble formation and content bias, based on the viewing and recommendation data collected from three types of accounts (Account A: political issue, Account B: environmental issue, Account C: random interests).

8.1 Political Issue-Oriented Account (Account A)

Account A primarily watched videos related to political issues (Trump/Biden speeches and U.S. political news), which quickly led to a homepage dominated by political recommendations. Notably, videos relating to Trump, Biden, the U.S. House, and other specific politicians and events were repeatedly recommended, with the

content often skewed toward either conservative or liberal perspectives.

Change Pattern: From the start of the experiment, the proportion of political content increased sharply, and by mid-to-late March, exposure to other types of content almost disappeared.

Filter Bubble Formation: Very strong. YouTube repeatedly recommended content in one political direction based on the user's preference, significantly limiting information diversity

Content Bias: Content repeatedly featured claims aligned with specific political positions (e.g., anti-immigration, right-wing perspectives), making it difficult for the user to receive a balanced viewpoint.

8.2 Environmental Issue-Oriented Account (Account B)

Account B focused on watching content related to climate change, global warming, and renewable energy. In the initial phase, environmental warnings, disaster simulations, and documentaries were most prominent; over time, the recommended content expanded to include related scientific and technical videos, global climate anomalies, and future scenario predictions.

Change Pattern: From the early stages of the experiment, recommendations for environmental crisis content were rapidly reinforced, with an increasing tendency toward sensational content emphasizing climate disasters and apocalyptic narratives.

Filter Bubble Formation: Weaker than the political account, but keywords associated with environmental issues (e.g., "end of the world," "climate clock," "melting glaciers") were repeatedly recommended, leading to topic bias.

Content Bias: Much of the content aimed to instill urgency through

emotional and disaster-centered frames, while alternative perspectives (such as technological solutions or policy analyses) were comparatively lacking.

8.3 Random Interest Account (Account C)

Account C was designed to watch a balanced variety of topics, such as world news, pop music playlists, simple cooking recipes, soccer highlights, and cute cat videos, following a set ratio. The analysis showed that YouTube consistently recommended a wide range of topics to this account, with little evidence of bias toward any specific topic.

Change Pattern: Recommendations remained evenly distributed according to viewing ratios; throughout the experiment, content categories such as music, cooking, pets, sports, and news were presented in a balanced manner.

Filter Bubble Formation: Very weak. Although the algorithm recognized repeated viewing patterns for certain topics, it maintained a circulatory structure among diverse content, preserving information diversity.

Content Bias: Information was provided with a routine and neutral character, without noticeable skew toward particular perspectives or directions.

8.4 Comparison Analysis Between Accounts

| Item | Account_A(Politics) | Account B(Environment) | Account C (Random) |
|------------------------|---------------------|------------------------|--------------------|
| Filter Bubble Strength | Very strong | Moderate | Very weak |

| | | | |
|-------------------------|-----------------------------|--------------------------------------|---------------------------------------|
| Content Diversity | Very low | Limited | Very high |
| Recommendation Bias | Strong political bias | Crisis/emotion-oriented bias | No notable bias |
| Topic Fixation Speed | Fast (within 2-3 days) | Fast (within 3-4 days) | None or slow |
| Representative Keywords | Trump, Biden, U.S. politics | Climate crisis, apocalypse, scenario | Cooking, cats, music, soccer, various |

8.5 Summary

The analysis of the collected data indicates that YouTube's recommendation algorithm exhibits clear differences in terms of content bias and information diversity according to users' topics of interest. For socially sensitive or dramatic subjects such as politics and the environment, the algorithm quickly reinforces filter bubbles by repeatedly recommending the same type of content. In contrast, accounts with random and everyday interests maintained relatively balanced recommendations, with a broad distribution of information. This suggests that the algorithm responds sensitively to users' initial behaviors, encouraging in-depth exploration of specific topics but also posing a greater risk of information bias.

9. Conclusion and Recommendations

9.1 Conclusion

This study empirically analyzed how YouTube's recommendation algorithm forms filter bubbles and media bias according to users' topics of interest. Three accounts—focused on political issues, environmental issues, and random interests—were created, and viewing data was collected over approximately two weeks to analyze the changes in recommended content.

The results show that YouTube's algorithm quickly offers biased recommendations centered on the user's initial interests, leading to limited information diversity and a distinct formation of filter bubbles. For the political issue account (Account A), content strongly aligned with specific political perspectives was repeatedly recommended, while the environmental issue account (Account B) mainly received sensational content focused on climate crises and disasters. On the other hand, the random interest account (Account C) showed greater variety in recommended content and weaker filter bubble effects.

These results demonstrate that YouTube's algorithm is highly sensitive to users'

viewing patterns, intensifying exploration within specific subjects. However, this structure can exacerbate information bias and confirmation bias, particularly in the context of social conflict issues.

9.2 Recommendations

Enhancing Algorithmic Transparency

YouTube currently provides little clear information about the criteria used for content recommendations. Making recommendation criteria and the functioning of algorithms more transparent would allow users to understand and better manage their own information flow.

Introducing ‘Diversity Algorithms’ to Mitigate Filter Bubbles

Recommendation algorithms should not focus solely on users’ areas of interest, but should also purposefully include opposing views and content from different topics. For example, incorporating ‘serendipity’ logic in the algorithm design could help mitigate filter bubble effects.

Strengthening User-Driven Content Exploration Features

YouTube’s structure relies heavily on automatic recommendations. Enhanced interfaces that enable users to broaden their own information horizons—such as ‘see recommendation reasons’ or ‘view opposing perspectives’—could contribute to media literacy.

Expanding Digital Media Education

In addition to platform-level improvements, users should be educated about the limitations and risks of filter bubbles. Education in digital citizenship and media interpretation is especially important for teenagers and young adults.

9.3 Limitations and Suggestions for Future Research

This study was conducted over a limited period (two weeks) and with a small sample size (three accounts), making it difficult to analyze long-term algorithmic changes or a wider range of topics. Future research should address the following points:

Tracking algorithmic changes over longer-term viewing patterns

Including more diverse topics such as health, economics, and education

Designing experiments that reflect demographic factors like age, gender, and

region

Investigating how algorithms interact with misinformation and sensational content

10. References

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