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# Auditing Entertainment Traps on YouTube: How Do Recommendation Algorithms Pull Users Away from News

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**ABSTRACT**

Recommendation algorithms that customize information feeds for individuals have raised concerns about exacerbating inequalities in news exposure among citizens. In response to these concerns, we conducted an audit study on YouTube to analyze the algorithmic impact on curating news versus other content topics. We examined over 1.7 million YouTube video recommendations audited in 2019 and developed novel analysis approaches including network analysis and Markov chains. Results show that recommendation algorithms may potentially redirect users away from news content through two influence pathways: (1) the "topical filter bubbles," wherein entertainment content has a higher probability of being recommended over news content in a self-reinforcing manner; and (2) "algorithmic redirection," wherein the probability of entertainment videos being recommended after a news video is much higher than that for the opposite. Overall, YouTube recommendation algorithms have a higher probability of recommending entertainment videos than news. The findings imply essential biases in algorithmic recommendations on digital platforms beyond amplifying users' preferences.

**KEYWORDS**
Filter bubbles; Markov chains; news exposure; recommendation algorithms; YouTube

Consumption of political news is largely divided among citizens (Delli Carpini & Keeter, 1996; Ksiazek et al., 2010). In particular, the high-choice media environment allows those highly interested in politics to get more news while at the same time offering opportunities for those less interested to opt out of such content, which exacerbates inequalities in political knowledge (Prior, 2007). The lack of requisite information potentially excludes audiences less interested in politics from engaging in public life or advocating for their interest in the democratic process (Kenski & Stroud, 2006).

In recent years, algorithm-driven media platforms, such as social network sites and search engines, have provided a significant share of the public's news exposure (e.g., Newman et al., 2022; Stocking et al., 2020), urging scholars to examine how this change will influence people's news consumption. Given that recommendation algorithms are supposed to provide individually customized media consumption (e.g., Davidson et al., 2010; Lazer, 2015; Liu et al., 2010), many are worried about whether such personalized curation prompts users to consume more content they prefer – for instance, more news to

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the politically interested but more entertainment to the politically uninterested – thus further widening existing gaps in political learning and participation among the public (e.g., Bennett & Iyengar, 2008; Van Aelst et al., 2017).

As one of the most influential social media platforms, YouTube has become a major news source for more than a quarter of Americans (Stocking et al., 2020). Also, its well-developed recommender system makes analyzing YouTube an initial step toward understanding the impact of algorithms on users' news exposure. Recent studies have examined radical content and misinformation recommendations on YouTube (e.g., Haroon et al., 2023; Hosseinmardi et al., 2021; Hussein et al., 2020), yet how YouTube's algorithms may affect users' exposure to news[1] compared to other topics has not been extensively examined. Thus, we designed this study to address this research gap. In light of the theoretical framework of sequential information flows (Pearson & Kosicki, 2017; Thorson & Wells, 2016; Vermeer & Trilling, 2020; Wu et al., 2021), we examined two influence pathways of algorithmic recommendation: *topical filter bubbles*, in which users are repeatedly directed to content that aligns with their interests,[2] and *algorithmic redirection*, by which users encounter a different type of content after consuming content of a given type.

We leveraged an auditing approach to examine YouTube's recommendations, as algorithm audits can provide a systematic appraisal of platform-level influences by controlling users' inputs (Metaxa et al., 2021). We employed a large-scale dataset that recorded both the meta-information and the user-independent recommendation of videos (~1.7 million pairs of seed videos and "Up Next" videos). The "Up Next" video is the first-ranked video recommended after a video is viewed and the most likely to be watched by YouTube users (see Hussein et al., 2020). The advantage of using this dataset is reducing the noise of historical viewing records and real users' profiles (see Davidson et al., 2010) as much as possible so that the results can optimally reflect the algorithmic effects of YouTube's recommendation system. We developed a mathematical model to calculate the transition probability matrix of video recommendations and combined it with network analysis to illustrate how the algorithms unevenly weighed different video categories to be recommended. Then, benefiting from the sequential pattern of video viewing, we employed a novel approach, Markov chains, to estimate how the likelihood of a video being watched based on recommendations varies across categories.

We find that topical filter bubbles partially exist on YouTube, as several video categories have a high tendency to be self-recommended as "Up Next." That is, users are likely to continue viewing content of the same category suggested by the algorithms. We also find asymmetry in "Up Next" recommendations. For instance, the algorithm is likelier to recommend an entertainment video after a user watches a news video than to recommend a news video after a user watches an entertainment video. Moreover, the Markov chains predict that entertainment generally wins over news. On average, the probability of entertainment videos to be recommended is three times higher than the probability of news videos to be recommended, indicating that no matter what users start with on YouTube, they are more likely to end up watching entertainment than news videos. This study enriches the extant research both theoretically and methodologically. By bringing in the perspective of news versus entertainment exposure and introducing novel computational approaches, this research explores the topic-level bias of YouTube recommendation algorithms and expands the conceptual framework of news exposure in the digital age. The paper concludes with a discussion of the implications for democracy and the generalizability of our conclusions to the recommendation algorithms of other digital platforms.

## Media Exposure As Sequential Flows: Two Influence Pathways of Algorithmic Curation

Media exposure can be examined in the framework of "curated flows," and algorithms are one of the major curators of concern (Thorson & Wells, 2016). The notion of "information flow" employed in this framework implies a sequential pattern of media exposure, which is also discussed by many scholars as "attention flow" (Wu et al., 2021), "news journey" (Vermeer & Trilling, 2020), and "way-finding" (Pearson & Kosicki, 2017). In other words, a user's online media exposure can be considered as their encounters with media content in sequential information flows.

The different media content that individuals encounter in sequence inspires a topic-level analytic perspective to understand the algorithmic effect. Particularly, the transition between pieces of media content reflects how a user's information flow is constantly directed from one type of content to another. When there is a transition in an information flow, the two media items are either of the same topic or not. This points to two influence pathways of algorithmic curation: *topical filter bubbles*, when the media items before and after a transition are of the same topic, and *algorithmic redirection*, when the media items before and after a transition are of different topics. We visualize this analytic framework in Figure 1 and explain the two pathways in the following sections.

### *Pathway One: Topical Filter Bubbles*

Providing audiences with their preferred content is at the root of the design of recommendation algorithms, as platforms' advertisement revenue depends heavily on user data

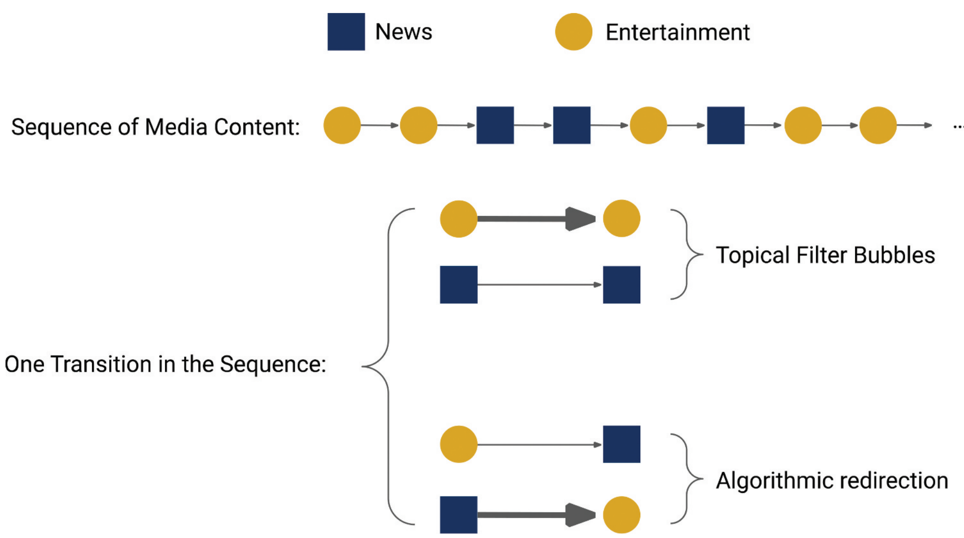


**Figure 1.** Algorithm-curated sequence of media exposure.
*Note*. We simplify the media content that people consume to a dichotomy of news and entertainment to illustrate the sequential process: If the user's before and after consumption is always the same content, he/she might encounter the topical filter bubble; if the user starts from one but ends up with the other, he/she might face algorithmic redirection. The arrow width reflects the relative likelihood that each transition will occur.

metrics, such as views, clicks, likes, and comments (Munger & Phillips, 2022). As such, platforms have good reason to recommend more of what users *like to* consume rather than what they *should* consume – the balanced and high-quality news information that keeps people informed of public affairs (Delli Carpini & Keeter, 1996).

This personalization effect of algorithms is theorized as "filter bubbles" (Pariser, 2011). Previous studies have examined whether algorithms facilitate ideological homophily in news consumption at the outlet level (e.g., Cardenal et al., 2019; Cinelli et al., 2021; Flaxman et al., 2016) but have found mixed evidence. Recently, researchers have turned to the content level and have found that recommendation algorithms selectively amplify right-wing and extreme political content (Hosseinmardi et al., 2020, 2021; Huszár et al., 2022; Whittaker et al., 2021) and formulate radical news bubbles for far-right YouTube consumers (Haroon et al., 2023; Hosseinmardi et al., 2020). Research also indicates misinformation bubbles on YouTube (e.g., Faddoul et al., 2020; Hussein et al., 2020). In short, concerns about filter bubbles remain a serious concern with regard to algorithm-driven media platforms, and particularly YouTube.

As noted by Pariser (2015), algorithmic personalization increases exposure not only to attitudinally congruent messages but also to topics of personal interest, such as sports and entertainment. The presence of the latter form of personalization, namely "topical filter bubbles," is indicated by some studies. For instance, Google News tended to suggest more sports news to a puppet account that was pre-trained with more sports content (Haim et al., 2018), and Facebook curated more news for users who were algorithmically inferred to have higher political interest (Thorson et al., 2021). Although the outputs of the recommendation algorithms in these studies were far from perfect personalization, the results reinforce concerns about the Matthew effect and related inequalities in news exposure on digital platforms (Kümpel, 2019, 2020). Meanwhile, as many people's behaviors on digital media platforms are not primarily driven by news-seeking purposes (Hanson & Haridakis, 2008; see also Hosseinmardi et al., 2020), these people are very likely to get immersed in entertainment content recommended by algorithms and potentially reduce their news consumption.

Moreover, topical filter bubbles are implied in the technical design of recommendation algorithms. The fact that watch history has a stronger effect than user demographics or geolocation information on YouTube's future recommendations of misinformation videos (Hussein et al., 2020) underscores the relative importance of the content of watched videos among the many factors that determine recommendation outputs (see also Johannesson & Knudsen, 2021; Knudsen, 2022). Topical categories, as one of a video's content-related attributes, are thus indicated to be essential predictors of recommendation outputs in this process. Hence, through the perspective of topical filter bubbles, we first investigate whether recommendation algorithms place greater weight on content of the same topic.

The current research is inspired by an exploratory study of the topological features of YouTube recommendations (Roth et al., 2020). Although Roth et al. (2020), p. did not comprehensively examine topical relevance in recommendations or provide theoretical explanations of such algorithmic effects, they offered an open-source dataset of recommendation records for further research. This study extends their analysis of YouTube's recommendations to explore topical filter bubbles. Given the lack of direct evidence substantiating topic-level filter bubbles, we ask the first research question as follows:

**RQ1.** How do YouTube algorithms recommend a video of the same topic after a video of this topic is finished?

### *Pathway Two: Algorithmic Redirection*

Algorithmic curation can redirect users to a type of content that is different from the one they just consumed, which indicates another possibility. Although some researchers contend that algorithmic curation can increase incidental news exposure for audiences who do not actively seek out news online (e.g., Fletcher & Nielsen, 2018b; Scharkow et al., 2020), these people's news consumption may not necessarily increase, especially considering the relative entertainment use (Kim et al., 2013). As entertainment is more popular than news, when algorithms recommend a different category of content, the probability of switching to entertainment content might be larger than that of switching to news. We name this influence pathway "algorithmic redirection."

If the likelihood of news content being recommended is lower than that of other content topics, even if people are being offered different kinds of media products by algorithms, the overall news exposure is likely to be limited. Thus, even though digital users encounter incidental news curated by algorithms, they may also get more entertainment content than previously, which detracts from the time spent consuming news. Given that people's attention is limited, the distraction posed by online entertainment content might undermine the overall amount of news consumption from all sources, including TV, newspapers, and news websites. In addition, recommendation algorithms directly reduce news consumption on the algorithmic platform by distracting users who originally started viewing news to entertainment content. Thus, whether users' news exposure is increased by algorithmic curation remains questionable.

To further demonstrate the process, we provide an example of media exposure on YouTube. After a user finishes watching a news video, the algorithms might recommend something different from news, such as entertainment content. Likewise, after another user finishes watching an entertainment video, YouTube might next suggest a news video. Although both situations seem possible, our daily use of YouTube suggests that the former happens often while the latter rarely does. This is due to the tiny fraction of news content in the information to which people are exposed, which indicates low political interests among many individual (see Allen et al., 2020; Wojcieszak et al., 2024). Therefore, the algorithmic recommendations on YouTube are likely to decrease one's likelihood of encountering news and divert news audiences to entertainment content. In this case, the uneven algorithmic curation across categories may also, to some extent, prevent some digital users from accessing political information or maintaining a healthy media diet. Hence, we ask the following research question:

**RQ2.** How do YouTube algorithms recommend videos across topical categories, especially between news and entertainment?

Overall, both topical filter bubbles and algorithmic redirection may play roles in shaping news exposure on YouTube. However, the interaction and potential influence these two pathways may have on each other is still unknown. Given the lack of prior work, we thus propose the following research question concerning the average effect of the recommendation algorithm:

**RQ3.** On average, how do recommendation algorithms influence news versus non-news exposure on YouTube?

## Methods

To understand the role that YouTube recommendation algorithms play in news consumption without involving users' historical activities, we conducted an audit study with a large-scale dataset collected from an anonymous querying process. (For more details on data collection and processing, see Section A in supplementary materials.)

### *YouTube and Recommendation Algorithms*

We focus on YouTube recommendation algorithms for several reasons. First, YouTube is an important news source for many Americans – about 26% of Americans get their news from YouTube and about 70% of YouTube news users regard YouTube as an important news source (Stocking et al., 2020), which makes the potential bias in YouTube's recommendation algorithms a serious problem. Second, YouTube is the most popular video website worldwide, with about 13.34 billion total visits as of November 2021.[3] Such high traffic indicates that people spend considerable time on YouTube; thus, analyzing YouTube is essential for offering suggestions to the public regarding media use. Third, YouTube has well-developed recommendation algorithms that aim to satisfy people by serving them videos they want to watch.[4] These facts make YouTube an exemplary platform to be analyzed.

### *Data*

The dataset used for this study was initially collected by Roth et al. (2020), who audited the recommendation process on YouTube by repeatedly crawling the suggested videos from the same seed video. The researchers first collected a set of distinct and highly watched YouTube videos as seeds and then visited each seed video about 20 times in an incognito approach to generate the recommendation results (For more details on data crawling, see Roth et al., 2020).

We used the same dataset that Roth et al. (2020) collected for reasons of reliability and feasibility. First, in this dataset, the recommended YouTube videos were crawled using a user-independent process. As algorithms utilize both users' digital traces and video information to generate recommendations (Davidson et al., 2010), a user's preferences and personal watch history may influence the outputs of algorithmic recommendations. By eliminating the effect of real users' data, the results better isolate the algorithmic effect and more accurately reflect the inherent technological bias of the platform. Second, the large-scale, open-access raw recommendation data they provided were collected with HTTPS queries from over one hundred IP addresses. The seed videos were also collected from various sources and not only represent the most popular YouTube videos but also cover a wide range of topics (see Figure S1 in supplementary materials). Since researchers can hardly access the complete pool of YouTube videos, this sample can best help us understand the info-ecosystem of YouTube.

For the purposes of this study, we extracted the "Up Next" recommendation dyads from the raw data collected by Roth et al. (2020), which contain 1,738,065 pairs of recommendation records.[5] The "Up Next" recommendation dyad refers to the algorithm-driven suggestion of an "Up Next" video from a seed video; the "Up Next" video is the first-ranked recommendation by YouTube algorithms. We focused on the "Up Next" video among the various recommendations for several reasons. First, focusing on the transition from the seed to the "Up Next" video rules out other factors that may impact the recommendation results (see Johannesson & Knudsen, 2021). Second, the "Up Next" video is one of the two main panels for users to encounter recommended results of YouTube algorithms (see Hussein et al., 2020), and the "Up Next" video usually auto-plays after a video finishes unless the user manually turns off this setting. For these reasons, YouTube audiences have a higher chance of viewing "Up Next" videos than other recommended videos.

We employed the YouTube video category as the proxy for the topic of each video. YouTube offers 15 video category labels, such as "news," "entertainment," and "how to & lifestyle." The category label attached to each video is primarily provided by video uploaders and is accessible to researchers in the HTML files of the video webpage. We show examples of different categories (Table S1) and how we conducted validation (Section D) in supplementary materials.

### *Analysis 1: Transition Probability Matrix*

To estimate the average likelihood that a video of a given category will be recommended by YouTube algorithms to any user, we first developed a mathematical model to calculate the transition probability matrix from the seed video category to the "Up Next" video category. The transition probability is defined as the average probability of a video of a specific category to be recommended by YouTube algorithms after a video of a specific category is played in an incognito mode. For instance, when the seed video category is "politics and news," the transition probability from "politics and news" to "entertainment" is the percentage of recommended entertainment videos out of all videos of all categories recommended. The calculation of the transition probability matrix is shown below.

$$P_{ij} = \frac{N_{ij}}{\sum_k N_{ik}}, \{i, j, k \in S\},$$

where $S$ represents the set of video categories provided by YouTube (excluding "not available"), $N$ represents the sum of videos that obey specific conditions in this sample dataset, $i$ represents the category of the seed video, $j$ represents the category of the "Up Next" video, and $P_{ij}$ represents the transition probability of category $j$ to be recommended when category $i$ is the seed. Thus, the transition probability matrix reflects the first-level likelihood distribution of recommendations between video categories.

### *Analysis 2: Network Analysis*

Based on the results of the transition probability matrix, we implemented a network analysis to further illustrate the asymmetric transition in recommendation dyads across video categories. Nodes in the transition network represent video categories, and edges represent the directional recommendation relationship between categories. The width of edges reflects the absolute numeric difference of transition probability in each recommendation dyad; the arrows of ties show the dominant transition direction in each pair of distinct categories.

For example, the numeric value of the edge width between "news" and "entertainment" is calculated by $P_{news\ to\ entertainment}$ minus $P_{entertainment\ to\ news}$, and the arrow direction aligns with $P_{news\ to\ entertainment}$, which indicates that the transition from "news" to "entertainment" is more likely than the opposite in YouTube algorithmic recommendations.

We also analyzed the in-degree centrality of each node and discussed its implications. The in-degree centrality in this network demonstrates the connectivity of one category to other categories in recommendation dyads. If one category has a low in-degree centrality with mostly outgoing transition arrows, this category is less prioritized by YouTube algorithms and its audiences are more likely to be pulled away from this type of content.

### *Analysis 3: Markov Chains*

The sequential pattern of recommendation relationships inspired us to use Markov chains to predict the average probability that a video category will be recommended. A Markov chain is a mathematical process used to predict future states given a transition probability matrix of a series of certain states and a sufficient number of transitions (Norris, 1998). Markov chains are widely applied in many domains, such as stock market prediction (Hamilton & Lin, 1996) and Google's PageRank method (Gleich, 2015).

Recently, communication scholars have noticed that Markov chains fit well with the sequential pattern of media/news use and have applied the approach to understanding how news audiences navigate across websites (Vermeer & Trilling, 2020). In this study, we used the posterior transition probability matrix calculated from the sample video set as the prior recommendation matrix for YouTube video categories. We were able to calculate the steady probability distribution of the categories to be recommended as "Up Next" videos with models in the R package "markovchain." The steady probability distribution in this study should be interpreted as the relative probability for any YouTube video category to be recommended compared to other categories. This probability does not refer to the actual likelihood of a category to come up in real-setting YouTube recommendations, but it reflects the *average* and *comparative* likelihood of a specific category to be recommended from any possible seed category without the user intervening in the algorithmic process. Therefore, the mathematical value for the steady probability distribution only represents how much more likely one category is to be recommended than another in general. We conducted this analysis to empirically determine whether YouTube recommendation algorithms tend to recommend entertainment content over news. If this was the case, the algorithmic bias in YouTube recommendations (i.e., pulling users away from news) would be identified, comprising the two influence pathways we separately characterized in the previous two parts of the analyzes.

# Findings

## *Topical Filter Bubble: Self-Reinforcing Topic Recommendations*

Based on the transition probability calculation (see Figure S2 in supplementary materials), our first analysis looked into the self-recommending probabilities for each YouTube video category. Figure 2 suggests that categories such as "automobile" (0.97), "sports" (0.96), "music" (0.88), and "game" (0.76) highly reinforce themselves; the probability of the "Up Next" video belonging to the same category as the seed video is higher than the probability of the "Up Next" video belonging to a different category. Compared to results from existing studies (e.g., Haim et al., 2018), we argue that these topics have a self-reinforcing tendency.[6] However, for categories such as "people and blogs" (0.21), "film" (0.20), "nonprofit" (0.12), and "travel" (0.05), the probability of self-reinforcement is far less than the probability of diffusing to another category.

Considering that these probabilities were one-time, direct calculations based on the sample, we bootstrapped the sample 1,000 times and estimated 95% confidence intervals for these probabilities (see Table S2 in supplementary materials). Thus, concerning the first research question, we find that YouTube recommendation algorithms have a self-

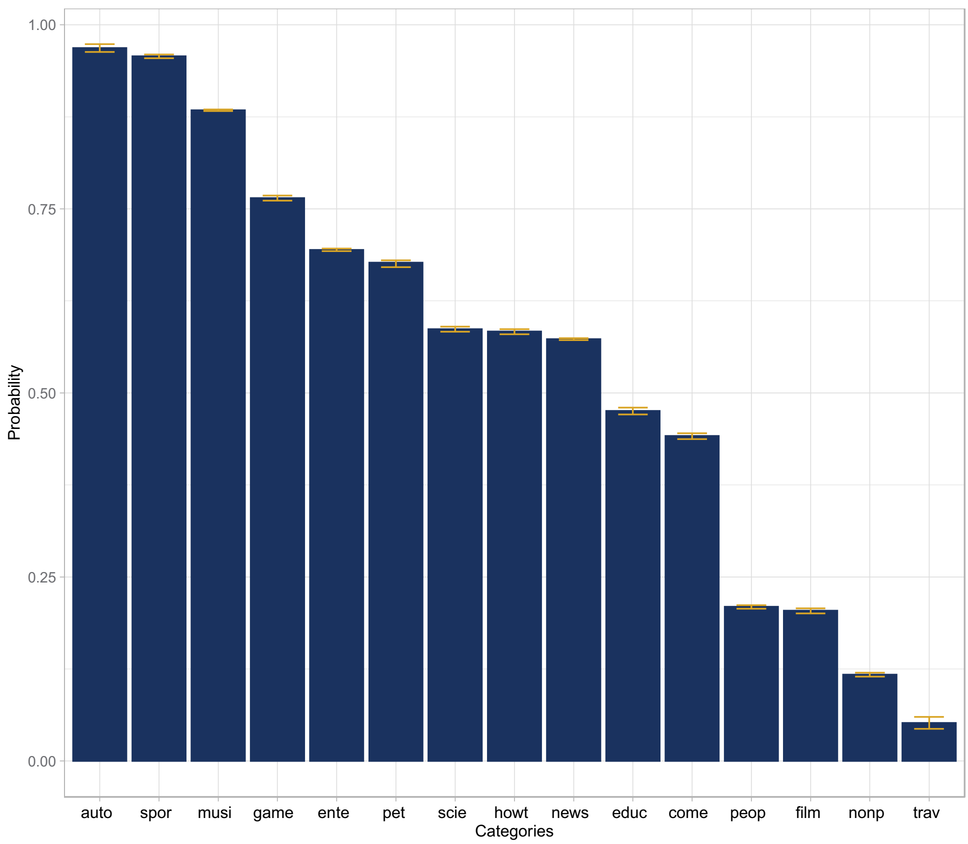


**Figure 2.** Self-recommending probability for each video category.
*Note*. The bars indicate the observed self-recommending probabilities. The 95% confidence intervals were calculated based on 1,000 times bootstrapping procedures.

reinforcing tendency for content on some, but not all, topics. In addition, YouTube tends to direct the audiences of some categories to different categories of content rather than content on the same topic.

## *Algorithmic Redirection: Asymmetric Transition Between Categories*

The analyzes in this section answer the second research question. We noticed differences in recommendation likelihood between video category pairs. For instance, there is a higher probability that entertainment videos will be recommended after news seeds ($P_{\textit{news to entertainment}} = 0.18$) than that news will be recommended after entertainment ($P_{\textit{entertainment to news}} = 0.03$). The asymmetric transition between video categories in recommendation dyads is presented in the transition difference network (Figure 3).[7]

The edge width reflects the difference between the recommendation probabilities in each dyadic group. The bolder the edge, the greater the difference. The arrowhead direction exhibits the afflux of recommendation likelihood, which also indicates the hierarchical

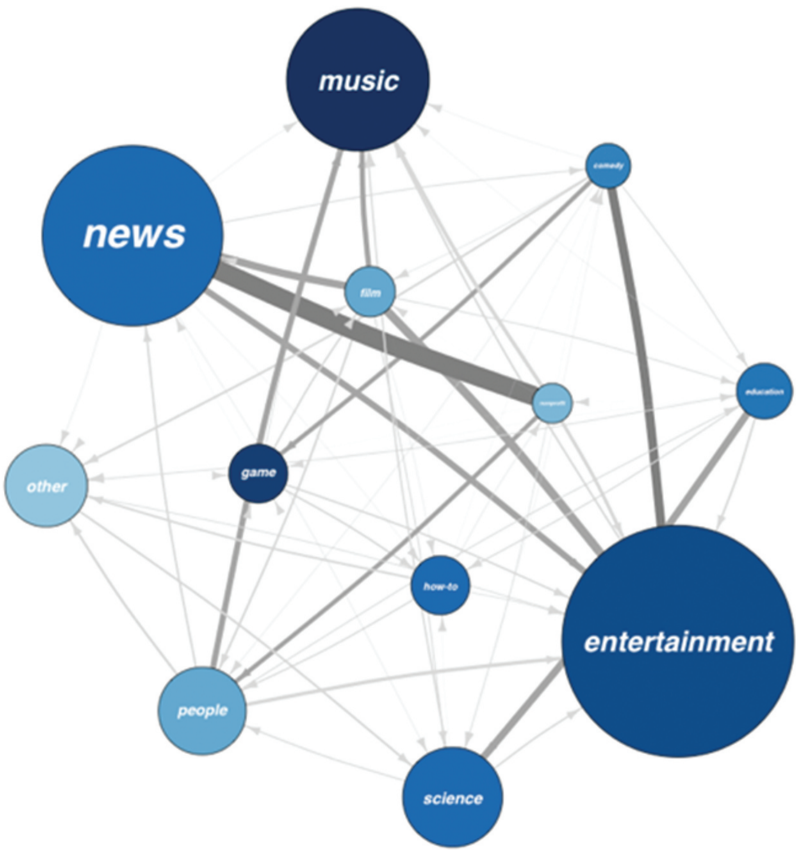


**Figure 3.** The network of transition probability differences between video categories.
*Note*. Nodes: video category; node size: degree centrality; node color: self-reinforcing probability. Edges: recommendation relationship; Edge width: the probability difference between the two-way transition; Arrowheads: the direction of the dominant transition.

structure in the category pairs. The category node to which the arrowhead points dominates the dyadic recommendation relationship, having a larger opportunity to be recommended when the other serves as the seed. Conversely, the category node from which the arrowhead emerges has a higher chance of being shadowed by algorithmic recommendations, and the audience of such a category is more likely to be distracted from continuing to view the same content.

As an example, in the dyadic recommendation between news and entertainment, the edge width is 0.15 ($P_{news\ to\ entertainment} - P_{entertainment\ to\ news} = 0.18 - 0.03 = 0.15$), which reflects the transition probability gap in the two-way recommendations of this pair. The arrow direction is from news to entertainment, which suggests that the transition from news to entertainment is likelier than the opposite. That is, entertainment is more likely to be recommended when news is the seed than news is to be recommended when entertainment is the seed.

Moreover, the size of the nodes visualizes the in-degree centrality of each category in the network (for more details about in-degree centrality values, see Table S3 in supplementary materials). The larger the node size, the higher in-degree centrality the corresponding category has in the transition network. When one node has a higher in-degree centrality, this node is more likely to attract audiences from other categories in recommendation relationships. Still using news as an example, news audiences on YouTube can easily be dragged to entertainment and other topics. YouTube recommendation algorithms have a higher chance of initiating a transition from news to entertainment than from entertainment to news, unveiling the problematic asymmetric transition between news and entertainment.

### *Combining Two Pathways: Steady Probability Distribution*

To answer the third research question, we estimated the steady probability of each video category being recommended via the Markov approach. The steady probability for a category to be recommended should be understood as the long-term average likelihood that an incognito user will encounter the category after watching a seed video of any category. This prediction implies an *ideal* state of distribution of the many video categories YouTube offers after sufficient transitions.

To assist in understanding the Markov chain predictions, we created the diagram shown in Figure 4 to demonstrate the simulated probability distributions across the transitions. If an incognito user starts with a news video, the likelihood of another news video being recommended decreases continuously as the "news-to-news" process repeats. However, the likelihood of an entertainment video being shown next will increase over time and eventually win over that of news. Compared to an alternative situation, if an incognito user starts with an entertainment video, though the likelihood of an entertainment video recommendation will gradually fall, it will consistently remain higher than that of a news recommendation. After a sufficient number of transitions, the probability distribution becomes stable; in other words, it reaches a steady probability distribution. While this simulation process does not include other algorithmic interventions, such as watch history, it amplifies the preference for entertainment in the YouTube recommendation system so that this hidden characteristic can be examined.

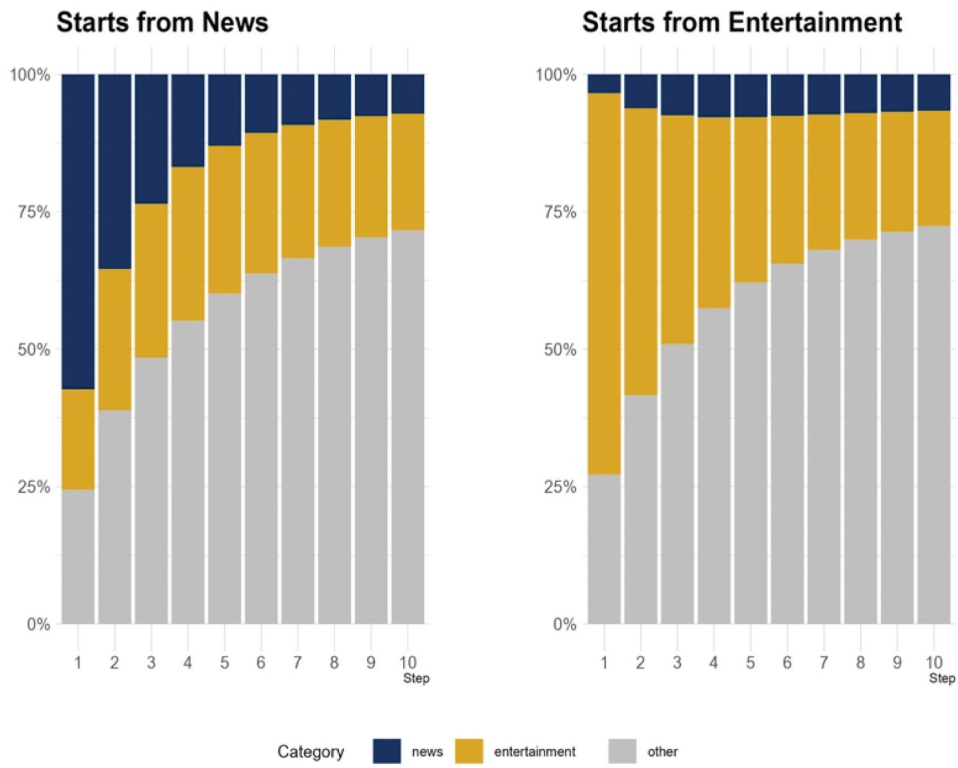


**Figure 4.** Recommendation probabilities starting from news and entertainment seeds.
*Note*. This diagram shows the simulated probability variation across the transition states in a complete algorithm-driven recommendation process. To simplify the process for exhibition purposes, we suppose two situations for a recommendation sequence to happen: from a news video (left) and from an entertainment video (right). The steps indicate the transition times for a supposed recommendation sequence.

Since different transition probability matrices can result in different steady predictions, we tried various strategies to group video categories and obtained different transition probability matrices (see Figures S2 to S5 in supplementary materials). We applied Markov chains in each case for robustness; the results are presented in Table 1. The probability of the news category to be recommended ranges from 0.05 to 0.11, while that of the entertainment category ranges from 0.16 to 0.24. The steady probability of entertainment is about two to three times that of news under all conditions. This result is possibly attributable to the fact that many seed categories have considerable transition probabilities of recommending entertainment videos. Therefore, the transition probabilities from other categories to entertainment videos together increase an individual user's likelihood of consuming entertainment on YouTube. Further interpretations and discussions specific to Markov chain steady probabilities can be found in the supplementary materials (Section C).

Briefly, our findings show that, on average, news videos generally have a relatively low probability of being recommended to YouTube users. Entertainment and other highly self-

**Table 1.** Steady Probability Distribution of YouTube Video Categories.

| | Raw Data | Strategy 1 | Strategy 2 | Strategy 3 | Strategy 4 |
|---|---|---|---|---|---|
| News & politics | 0.051 | 0.060 | 0.064 | 0.113 | 0.062 |
| Pet | 0.008 | | | | 0.009 |
| Automobile & vehicles | 0.149 | | | | 0.168 |
| Entertainment | 0.163 | 0.189 | 0.195 | 0.241 | 0.547 |
| Film | 0.027 | 0.030 | 0.032 | | |
| Comedy | 0.020 | 0.023 | 0.024 | | |
| Game | 0.036 | 0.045 | | | |
| Music | 0.272 | 0.326 | | | |
| Nonprofits & activism | 0.007 | 0.008 | 0.008 | | 0.008 |
| People & blogs | 0.047 | 0.058 | 0.061 | | 0.052 |
| Science & technology | 0.048 | 0.059 | 0.065 | | 0.053 |
| Sports | 0.088 | | | | |
| How to & style | 0.054 | 0.076 | | | 0.065 |
| Travel & events | 0.005 | | | | 0.006 |
| Education | 0.026 | 0.032 | 0.034 | | 0.030 |
| Others | / | 0.094 | 0.518 | 0.646 | / |

To test the robustness of the Markov chain results, we grouped the categories following different strategies and generated different transition probability matrices.
Raw data: We used the original category labels offered by YouTube.
Strategy 1: Considering the low share in the sample (less than 2%), we group "pet," "automobile," "sports," and "travel" as "others.."
Strategy 2: Some categories rarely recommended news videos in the sample (probability < .01). We grouped these categories ("pet," "automobile," "game," "music," "sports," "how to," and "travel") as "others.."
Strategy 3: We combined all categories other than "news" or "entertainment" as "others.."
Strategy 4: Under the broad definition of "entertainment" in the field of political communication, we combined "entertainment," "film," "comedy," "game," "music," and "sports" as "entertainment."

reinforcing topics have a higher recommendation probability than news content, as predicted by the Markov chains, thus answering RQ3.

## Discussion

By auditing YouTube's "Up Next" videos, this study examines the characteristics of the recommendation algorithms that may affect users' news exposure and consumption on the platform. We examined two algorithm-driven influence pathways: topical filter bubbles, which might trap users within topical silos of personal interest, and algorithmic redirection, which might divert users from political news to entertaining content. As predicted by Markov chains, overall, entertainment videos are more likely to be recommended than news.

Our findings have many theoretical implications. We first notice that both pathways may lead to decreased news consumption on YouTube. We find a stronger self-reinforcing tendency in many entertaining topics (e.g., sports, music, and games) but a weaker one in news and politics, indicating that topical filter bubbles can be a more serious concern for audiences who primarily prefer to consume entertaining content. These users' consumption of such content will be further amplified by both self-motivation and algorithmic recommendations. In this case, heavy viewers of entertaining content may reduce their exposure to news and political information. At the same time, news videos are less likely to be self-recommended, and entertainment videos, either broadly or narrowly defined, are more likely to be recommended than news. Thus, even audiences who primarily seek news information on YouTube can easily get directed from news by other light content. Through this mechanism, the news exposure of these users is also reduced by algorithms, though via a different pathway from that of entertainment viewers.

These speculative consequences indicate that the role of algorithmic recommendations goes beyond amplifying users' personal preferences, as Thorson et al. (2021) addressed in their earlier work. Besides personalization effects, YouTube's algorithms may have essential biases favoring entertainment recommendations, which may reduce people's news exposure on the platform no matter the specific purpose of use. In this case, besides the interest-driven divide in news consumption as Prior (2007) was worried about and the Matthew effect on digital news exposure (Kümpel, 2020), recommendation algorithms that prioritize entertainment content may lead to asymmetric influence to audiences of news versus entertainment: people who are more interested in news and politics might be exposed to slightly more news than the other group, but their overall amount of news exposure might not increase significantly due to the algorithmic redirection; on the other hand, the less interested group can easily be exposed to ample entertainment content as a result of topical filter bubble effects, and meanwhile, their exposure to news stays at a minimal level.

We also argue that understanding technical characteristics of recommendation systems paves new ways to examine the effects of algorithmic curation on news exposure in the hybrid media environment (Chadwick, 2017). As one of the major curators of individuals' information flows (Thorson & Wells, 2016), algorithmic recommendations with initial biases toward entertainment content may facilitate "de facto news-avoided environments" wherein digital users incidentally reduce their news exposure, a counter-prediction of incidental exposure (e.g., Fletcher & Nielsen, 2018a, 2018b), and urges further research to reconcile the dispute.

Furthermore, such a platform-wide bias toward entertainment is deeply rooted in the economic logic of media suppliers (Munger & Phillips, 2022). As digital platforms are operated by technology companies, the goal of recommendation algorithms is to provide content that audiences may like to consume, as more views and engagement from users can help increase revenue and attract more investment. Hence, the economic goal encourages algorithm designers to privilege entertaining content over news. Even though companies react to societal concerns – for instance, YouTube has rolled out policies to regulate misinformation on their platform – their top-down adjustments on algorithmic outputs have thus far not been very effective (e.g., Faddoul et al., 2020). This case suggests that algorithmic biases in recommendation systems are not easy to recognize or adjust, which calls for more scholarly attention to this issue.

In practice, individuals' news exposure is co-determined by multiple curators, including both human decisions and algorithmic recommendations. Different from many studies that consider effects involving various actors, the auditing approach allows us to isolate algorithmic influences from user preferences. Thus, our study serves as an essential first step in exploring the primary bias embedded in algorithmic systems by controlling for human inputs, which contributes to future research on examining how different curators interact in influencing information flows.

Additionally, we hope to underline the methodological novelty of employing Markov chains to examine the curated flows in this study. As the sequential pattern of information flows meets assumptions for Markov chains, we believe this perspective will motivate future studies to widely apply this approach in other analyzes and potentially inspire theoretical innovations in understanding digital news behaviors in other communication contexts (see also Vermeer & Trilling, 2020).

This study has some limitations. First, its ecological validity is limited. Since we analyzed only the data collected in an incognito mode, it remains unknown whether the algorithmic bias we identified will significantly impact real users' consumption on YouTube, given that one's news consumption is an interplay between algorithmic curation and the user's selection. Further observational studies should also consider user behaviors. Another shortcoming is that we only provide evidence from a single-platform recommender, which is unlikely to be generalizable to algorithm bias in other recommendation systems. We call for more studies to explore other platforms, which will advance the understanding of the algorithmic effect in the current digital environment. Additionally, we acknowledge that our study primarily focused on broad content categories. The influence of algorithms on more detailed content clusters, such as specific issues, is also worth investigating in future research.

## Notes

1. We are aware of current debates around the blurring boundaries between news and entertainment in the hybrid media environment (e.g., Edgerly & Vraga, 2020; Williams & Delli Carpini, 2011). In this study, "news" is defined in accordance with a more conservative perspective: the political information that is vital for informed citizenship and representative democracy (e.g., Delli Carpini & Keeter, 1996).
2. The term "topics" ("topical") in this paper refer to broader content categories, such as news, entertainment, music, movie, and games.
3. See https://www.statista.com/statistics/1201880/most-visited-websites-worldwide/
4. See https://indianexpress.com/article/explained/youtube-recommendations-explained-7587523/ and https://blog.hootsuite.com/how-the-youtube-algorithm-works/#A_brief_history_of_the_YouTube_algorithm
5. The unidentified data and analysis scripts can be accessed from the following link: https://osf.io/r85p9/?view_only=930b97a05ae5474fa7a5ba01419afaa3.
6. In an audit study of Google News, Haim et al. (2018) found the personalized recommendation probabilities for news/politics, entertainment, and sports were 52%, 17%, and 33%, respectively. Compared to these results, YouTube shows higher probabilities of recommending the video with the same categories, which indicates stronger topical filter bubble effects.
7. Considering the low proportion of certain categories in the sample, which may result in a relatively low accuracy for the measure of transition probabilities, we group "pet," "automobile," "sports," and "travel" into a single group, "others"

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## Disclosure Statement

No potential conflict of interest was reported by the author(s).

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## Data Availability Statement

The data that support the findings of this study are available from the corresponding author, upon reasonable request.

## Open scholarship

This article has earned the Center for Open Science badge for Open Data. The data are openly accessible at https://doi.org/10.1080/10584609.2024.2343769

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