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Article

What's "Up Next"? Investigating Algorithmic Recommendations on YouTube Across Issues and Over Time

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Abstract
YouTube's "up next" feature algorithmically selects, suggests, and displays videos to watch after the one that is currently playing. This feature has been criticized for limiting users' exposure to a range of diverse media content and information sources; meanwhile, YouTube has reported that they have implemented various technical and policy changes to address these concerns. However, there is little publicly available data to support either the existing concerns or YouTube's claims of having addressed them. Drawing on the idea of "platform observability," this article combines computational and qualitative methods to investigate the types of content that the algorithms underpinning YouTube's "up next" feature amplify over time, using three keyword search terms associated with sociocultural issues where concerns have been raised about YouTube's role: "coronavirus," "feminism," and "beauty." Over six weeks, we collected the videos (and their metadata, including channel IDs) that were highly ranked in the search results for each keyword, as well as the highly ranked recommendations associated with the videos. We repeated this exercise for three steps in the recommendation chain and then examined patterns in the recommended videos (and the channels that uploaded the videos) for each query and their variation over time. We found evidence of YouTube's stated efforts to boost "authoritative" media outlets, but at the same time, misleading and controversial content continues to be recommended. We also found that while algorithmic recommendations offer diversity in videos over time, there are clear "winners" at the channel level that are given a visibility boost in YouTube's "up next" feature. However, these impacts are attenuated differently depending on the nature of the issue.

Keywords
algorithms; automation; content moderation; digital methods; platform governance; YouTube

Issue
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1. Introduction

YouTube is a dominant platform for news consumption, self-education, and opinion formation via video (Burgess & Green, 2018). A large proportion of YouTube content is suggested or automatically delivered to users via the platform's automated recommendation systems (Solsman, 2018), which have been criticized for amplifying misinformation, harmful content, and extreme views (Bergen, 2019; Roose, 2020). In particular, the platform's "up next" or "suggested videos" feature, which displays and automatically plays a sequence of videos following the one that is currently playing in the main window, has been criticized for leading people down recommendation chains ("rabbit holes") of disturbing content (O'Callaghan et al., 2015), and contributing to political radicalization (Lewis, 2018).

The recommender system behind YouTube's "up next" feature has evolved over time and comprises multiple components including: the "related videos" algorithm (in use in various iterations for more than a decade; see Davidson et al., 2010); personalized "recommended videos" related to the user's watch history; and videos drawn from the same channel as the currently playing video. It typically prioritizes those videos that have been recently uploaded which have a high number of views and long average watch times, and it considers the popularity of a video by including viewer satisfaction measures such as likes and dislikes (Covington et al., 2016). Increasingly, the system relies on deep learning approaches to improve the "quality" of recommendations and to increase user engagement (Zhao et al., 2019).

A central concern regarding YouTube's "up next" feature is that, in service of the goal of increasing "engagement," it may tend to select videos that are highly evocative or provocative, including radical, alarmist, or otherwise extreme content (see for example a study by Mozilla Foundation and UC Berkeley scholars—Faddoul et al., 2020). By way of responding to these concerns, in 2019, the company announced it had made three significant "improvements" to its recommendation systems. First, they were updated to promote more diverse content by suggesting videos from a wider range of topics to avoid suggesting "too many similar recommendations, like seeing endless cookie videos after watching just one recipe for snickerdoodles" (The YouTube Team, 2019a). Second, changes were made so that "borderline content" would be demoted by the recommendation algorithms, so as to "reduce the spread of content that comes right up to [but does not cross] the line" of violating the platform's community guidelines (The YouTube Team, 2019b). Third, changes were made to increase the amplification of "authoritative voices" (The YouTube Team, 2019c), for example, for some breaking news events, YouTube's algorithms will prioritize videos published by trusted news outlets (The YouTube Team, 2019c).

In this article, we demonstrate a new method and generate new empirical evidence that contributes to public oversight of the operations of YouTube's suggested video feature, especially regarding potentially controversial sociocultural issues. We explore patterns in the recommendations made by YouTube's suggested videos feature over time for keyword search terms connected to sociocultural issues: "coronavirus," "feminism," and "beauty." By studying the algorithmic amplification of content connected to these terms we are able to provide empirical evidence for evaluating the claims made by critics and the counterclaims made by YouTube about the role of its "up next" feature in the amplification (or lack thereof) of problematic, authoritative, and diverse media content.

2. Social Media Recommender Systems, Exposure Diversity, and Platform Observability

Over the last decade, social media has emerged as important elements of a "hybrid media system" (Chadwick, 2017) that continues to reconfigure how information is created, distributed, and consumed. While there is technically more content available to audiences than ever before, in practice algorithms play a pivotal role in influencing users' exposure to a range of diverse media content and information sources, which is an important element of a media environment supportive of deliberative democracy (Glasser, 1984; Helberger, 2012; Horwitz, 2005; Napoli, 1999). Scholars and public commentators have argued that platforms' focus on maximizing "engagement" (giving users more of what they seem to want) can limit users' exposure to different points of view (Pariser, 2011; Sunstein, 2001), which in turn may lead to the hardening of extreme views, and political radicalization (Helberger, 2019). However, the supporting evidence is mixed. While some studies indicate that the algorithmic promotion of extremist and far-right content can lead users through recommendation chains of increasingly extreme content (e.g., Mozilla Foundation, 2020; Ribeiro et al., 2020), others suggest that actors exploit recommender systems by creating content to fill "voids," thereby gaining outsized attention for extreme content (Golebiewski & boyd, 2019, p. 29). Still others conclude that users encounter far-right content mostly through their own searches, indicating a level of pre-existing demand for extreme or radicalizing content, and that recommendation systems (including search engines) play a subsidiary role in its delivery (see e.g., Ledwich & Zaitsev, 2020). A number of scholars have suggested that excessive concern about algorithmic recommendation and associated personalization limiting users' exposure to diverse content may not be warranted (e.g., Haim et al., 2018; Möller et al., 2018), and more broadly, that additional work needs to be conducted to conceptualize standards for "diversity" in critiques of recommender systems' outputs (Loecherbach et al., 2020; Nechushtai & Lewis, 2019; Vrijenhoek et al., 2021). For example, questions of social diversity (i.e., the representation in both content and production of a range of class- and identity-based communities) are increasingly relevant to policy and practice, and platforms' use of "diversity" without definition (e.g., Zhao et al., 2019) illustrates the limits of corporate attempts to provide transparency relating to complex sociocultural and policy issues.

Despite these diverging views, there is consensus around two important aspects of platforms' recommender systems and how to hold them accountable. First, it is widely accepted that algorithms' opacity (Diakopoulos & Koliska, 2017)—or what Pasquale (2015) calls the "black box" of algorithmic decision making—makes it difficult to curtail platform power, which has motivated a growing body of empirical research interested in studying algorithms *from the outside*. This includes methods such as “reverse engineering” (Diakopoulos, 2015), “scraping audits” (Sandvig et al., 2014), “everyday algorithm auditing” (Shen et al., 2021), small-scale observation (Bucher, 2012), and systematic large-scale observation (Rieder et al., 2018). Second, debates around how to hold the media accountable in general, and social media in particular, tend to focus on calls for greater transparency for regulatory inspection (Diakopoulos, 2016; Pasquale, 2015). However, the technical complexities of digital platforms pose unique challenges that complicate the effectiveness of transparency as a tool for generating knowledge about “what is hidden” (Ananny & Crawford, 2018; Rieder & Hofmann, 2020, p. 5).

“Observability” has been proposed as a path “to deal more systematically with the problem of studying complex algorithmic systems” (Rieder & Hofmann, 2020, p. 1). Whereas transparency invokes the idea of the algorithm as a mathematical formula which, if revealed for oversight, could lead to a better understanding of platforms’ roles in the realization of media diversity, for example, observability as a tool for better regulation recognizes platform algorithms as complex socio-technical systems. The performance of platform algorithms that use deep learning models is influenced by multiple factors: developers’ design choices, built-in randomness, business practices, content creators’ optimization tactics, and audience viewing and engagement patterns. The idea of “algorithmic cultures” has been proposed to describe the variety of factors and agencies involved in generating algorithmic outcomes (McKelvey & Hunt, 2019; Rieder et al., 2018; Seyfert & Roberge, 2016) and to tackle the difficult task of assessing the social impacts of platformization. Rieder and Hofmann (2020, p. 22) advocate for “regulating for observability.” They stress the need to observe platform behaviour over time and to institutionalize “processes of collective learning” to develop “the skills that are required to observe platforms” (p. 24).

This article aligns with the idea of “platform observability” and presents a method for observing and studying YouTube’s recommendation “algorithmic cultures” over time. The following research questions inform our study: What kind of media does YouTube frequently recommend over time in relation to specific sociocultural topics? Are there patterns in these recommendations that can help answer longstanding questions about media diversity? Are there patterns in these recommendations that can improve our understanding of how YouTube operationalizes “media authority” in relation to different sociocultural issues? Drawing on Rieder et al.’s (2018) method for studying “ranking cultures” on YouTube—which they define as “unfolding processes of hierarchization and modulation of visibility that call on users, content creators and a platform that intervenes and circumscribes in various ways” (p. 52)—we use a combination of computational and qualitative methods to investigate the different factors that converge in producing recommendations in the “up next” section. We are attentive to the “moments of choice” that find their form in algorithmic operations (Rieder, 2017, p. 113); that is, since the platform can only show a limited number of videos in the “up next” interface (between 4 and 60), there is a complex process of selection that factors a wide range of features to provide “more quality information to users” (YouTube, n.d.). These processes of selection rely on sophisticated deep learning approaches that learn from user feedback to assess the “quality” of content (e.g., popularity and “freshness” of videos; see Covington et al., 2016), refine for personalization, improve the diversity of recommendations (Zhao et al., 2019), raise “authoritative voices,” and demote “borderline content” (The YouTube Team, 2019c).

In this study, we were also interested in understanding how the platform’s cultures of use influence YouTube’s “up next” feature in practice and for different topics. We paid attention to “platform vernaculars”: that is, the specific practices emerging from platforms’ unique technical affordances and how users appropriate them in practice (Gibbs et al., 2015). In the case of YouTube, examples of platform vernaculars are users’ tactics to gain algorithmic visibility: from word choices in titles and thumbnails, to other optimization techniques such as being an active content creator and building a network on the platform via featuring and subscribing to other channels (Bishop, 2019). Following Rieder et al.’s (2018, p. 54) suggestion that YouTube’s ranking practices “cannot be easily detached from the specificities of concrete issues,” we also consider the role of “issue vernaculars”, by which we mean the ways that platform vernaculars are articulated and given form in the context of specific social, cultural, and political issues. For example, for topics such as Islam, highly active and controversial Islamophobic “niche entrepreneurs” gain exceptional levels of visibility on YouTube (Rieder et al., 2018, p. 64). Our focus on platform and issue vernaculars complements existing literature that has focused on platform design as a central requisite to facilitate or constrain exposure to media diversity (Helberger, 2011).

Our aim in selecting the topics Covid-19 (“coronavirus”), feminism (“feminism”), and beauty (“beauty”) was to focus on contemporary issues of public concern that have been at the center of controversies on YouTube, and where YouTube recommendations potentially play a role in shaping public perception and understanding of these topics. “Coronavirus” was selected due to the relevance of Covid-19 as a news topic during the time period studied, one beset by misinformation which therefore might trigger YouTube’s amplification of “authoritative sources.” We selected “feminism” as a highly political and contentious issue on YouTube (Burgess & Matamoros-Fernández, 2016; Siddiqui, 2008), which might therefore provide indications of content and perspectival diversity. In contrast, “beauty” was selected as a contested issue that is less frequently the subject of mainstream political discourse, and so could provide a comparison to topics more strongly associated with controversial political issues.

3. Methods

The methods we use in this article provide the basis for a crucial intervention in the space between technology press speculation and folk theories about algorithms on the one hand, and abstract critical theory on the other. To observe what the algorithms underpinning YouTube's "up next" section "do," we follow Rieder et al.'s (2018) approach to studying algorithmic outcomes through description instead of aiming at identifying " 'hard' moments of causality" (p. 53). Along with Rieder et al. (2018), we are inspired by Savage's (2009) idea of descriptive assemblage—"where processes of creativity, conceptual innovation, and observation can be used to mobilize novel insights" (p. 170)—and use it as a strategy to make sense of broader forms of agency involved in algorithmic power.

Our method provides two main vantage points from which to study algorithmic cultures in general, and recommendations on YouTube specifically. First, we consider time as a crucial aspect of "platform observability" and hence examine YouTube's "up next" feature over time to move away from the "snapshot logic" (Rieder & Hofmann, 2020, p. 7) underlying many studies on algorithmic accountability (see Airoldi et al., 2016; O'Callaghan et al., 2015; Ribeiro et al., 2020; Schmitt et al., 2018). Second, we study YouTube recommendations across different sociocultural topics because we consider that "good" recommendations can only be envisioned and operationalized in relation to specific issue domains (Rieder, 2020, p. 334). A significant limitation in our study, however, is that we are unable to account for the effects of user preferences in how YouTube suggests what videos to watch next.

3.1. Data Collection

We designed two separate gatherers to collect the data for this research. Gatherer 1 used the "search: list" endpoint of the YouTube API to collect recommended videos and their rankings for each of our three keywords. We set the "order" parameter to "upload date," which is one of the user-facing search settings in YouTube's website and mobile applications. Our rationale for selecting "upload date" as a ranking criterion responded to our interest in gathering videos from channels that were active in creating content during the period studied. We collected the 20 top results (globally) for each of our three queries from 7 March to 22 April 2020, once per day at approximately the same time each day. Our cut-off date represents the last date we were able to extract reliable data. During the study period, YouTube made changes to its API that prevented us from searching for newly uploaded videos in real-time.

Gatherer 2 was used to collect the recommendation chains (the sequence of suggested videos) that followed each of the videos gathered daily by Gatherer 1. Drawing on research suggesting that users pay more attention to items ranked at the top of lists (Jugovac & Jannach, 2017), we collected the top five recommendations for each video, going three levels deep (see Figure 1). This yielded a daily collection of up to 3,100 recommended videos per query (the sum of related videos collected every day for step 1, step 2, and step 3), and a total collection of up to 145,700 recommended videos (up to 3,100 recommended videos per 47 days of data collection). Gatherer 2 sent requests from an Australian-based IP address, without any identifying cookies. This means that we did not collect "recommended for you" videos, but we were able to receive localized suggestions in the "up next" feature. Our web-interface scraping method likely explains why English-language sources were so heavily present in our data and why Australian channels were recommended for queries.

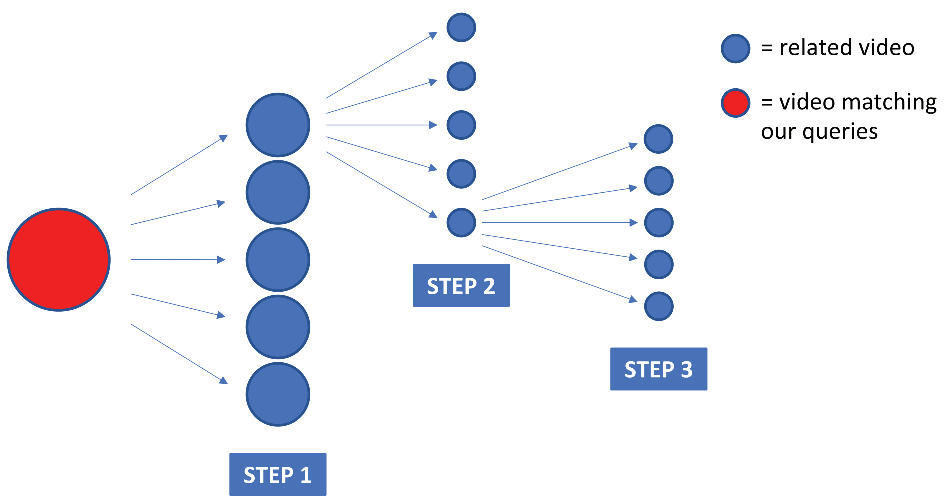

Figure 1. A schematic overview of our scraping method.

3.2. Data Analysis

For the data analysis, we combined data visualizations and qualitative analysis to identify patterns in how YouTube preferences certain content in the "up next" feature. Using the RankFlow tool (Rieder, 2016), we created flow diagrams that made changes in the top 10 most recommended videos and channels observable for analysis. All channels and videos included in the rankflows were recommended at least twice per day. Our aim with this approach was to understand the video and channel "winners" for each query; that is, those videos and channels most recommended over time and across steps in the chain. The visual inspection presented in Figures 2, 3, and 4 helps to identify patterns and operates as a starting point for in-depth investigation. The flow diagrams allow us to answer specific questions, such as whether certain unique channels are frequently recommended across days and steps. As seen in Figure 1, this is indeed the case (the flow diagrams exhibit a high number of blue/purple/red "waves" for the channel diagrams, which the RankFlow tool displays when it identifies that a unique video or channel appears on different days over time).

For the qualitative analysis, we looked for patterns in terms of media authority or popularity (proxies for quality), and we looked for patterns in perspectives that might give indications as to content diversity. To make sense of recommendation patterns for each of our topics, we were also attentive to platform and issue vernaculars. We took similar approaches for both channels and videos, but a greater emphasis was placed on channels in order to assess how "authoritativeness" is operationalized by YouTube's "up next" feature in relation to each of our queries. In our qualitative investigation, we also privileged patterns observed in step 1 of the recommendation chain. We considered those channels and videos surfaced in step 1 as the clear "winners" in terms of visibility—their position in the chain means they are most likely to be watched via autoplay or selected for play by a user.

For channels, we focused on the top 20 most recommended media sources over time and across steps for each of our queries (see Tables 1, 3, and 5). Since YouTube mentions "authoritative voices" in its policies but does not define the term, we looked at channel subscriber count, relevancy of the channel topic in relation to our queries, and frequency of upload at the time of our data collection as proxies for "media authority." For example, we considered subscriber count as an indicator for professionalization (see Rieder et al., 2020) and, hence, a metric potentially linked to a channel's authority, at least within YouTube's attention economy. We drew on YouTube's own "benefit levels" classification for channels to account for professionalization: "graphite" status (channels with less than 1,000 subscribers) gives content creators access to basic tools; surpassing the threshold of 1,000 subscribers, "opal" status, gives channels access to monetization through advertisements; "bronze" status (>10,000 subscribers) allows channels to access professional production tools; and "silver and up" (>100,000 subscribers) gives content creators the ability to have their own YouTube partner manager and receive Creator Awards (YouTube Creators, n.d.). To break down the rather broad "silver and up" tier, we added "gold" (>1,000,000–<10,000,000 subscribers) and "diamond" status (>100,000,000 subscribers) to YouTube's official channel classification system. In terms of media diversity signals, we considered channels' geographic regions and paid attention to questions of representation among the content creators most recommended for the "beauty" and "feminism" queries.

For videos, we focused on the top five most recommended videos over time and across steps for each of our queries (see Tables 2, 4, and 6) and we assessed their popularity, relevancy, and recency, through an analysis of their view counts, user engagement metrics, and upload dates, respectively. In terms of diversity of viewpoints, for "coronavirus," we focused on media frames (e.g., the use of militaristic language to describe the pandemic); for "feminism," we paid attention to whether the most recommended videos had a feminist or an anti-feminist stance; and for "beauty," drawing on the work of Bishop (2018), we were interested in examining how gendered and commercial logics influenced the content recommended for this query.

4. Findings

4.1. General Patterns Observed

Our visual analysis reveals two clear patterns in recommendations in the "up next" section over time, across queries, and across steps in the recommendation chain: (a) there is a higher level of variation in recommended videos than in recommended channels, (b) there is always more variation in suggested content at step 1 than at steps 2 and 3 (see Figures 2, 3, and 4). For each of our queries, there are clear "winners" at the channel level (media source) that are given a visibility boost by YouTube's recommendation algorithms—some channels are recommended repeatedly each day and consistently over time and down the chain (see Tables 2, 4, and 6).

4.2. Coronavirus

For "coronavirus," the platform prioritizes US news media outlets in the "up next" section as "authoritative" media in relation to Covid-19 (see Figure 2 and Table 1). Especially in step 1, while only 5.7% of videos (n = 16) were recommended on two or more days during the period studied, 49.4% of channels (n = 39) were recommended on more than one day. Mainstream news media channels falling within the "gold" or "diamond" tier dominate at each step, with NBC News the clear "winner" across the entire recommendation chain (see

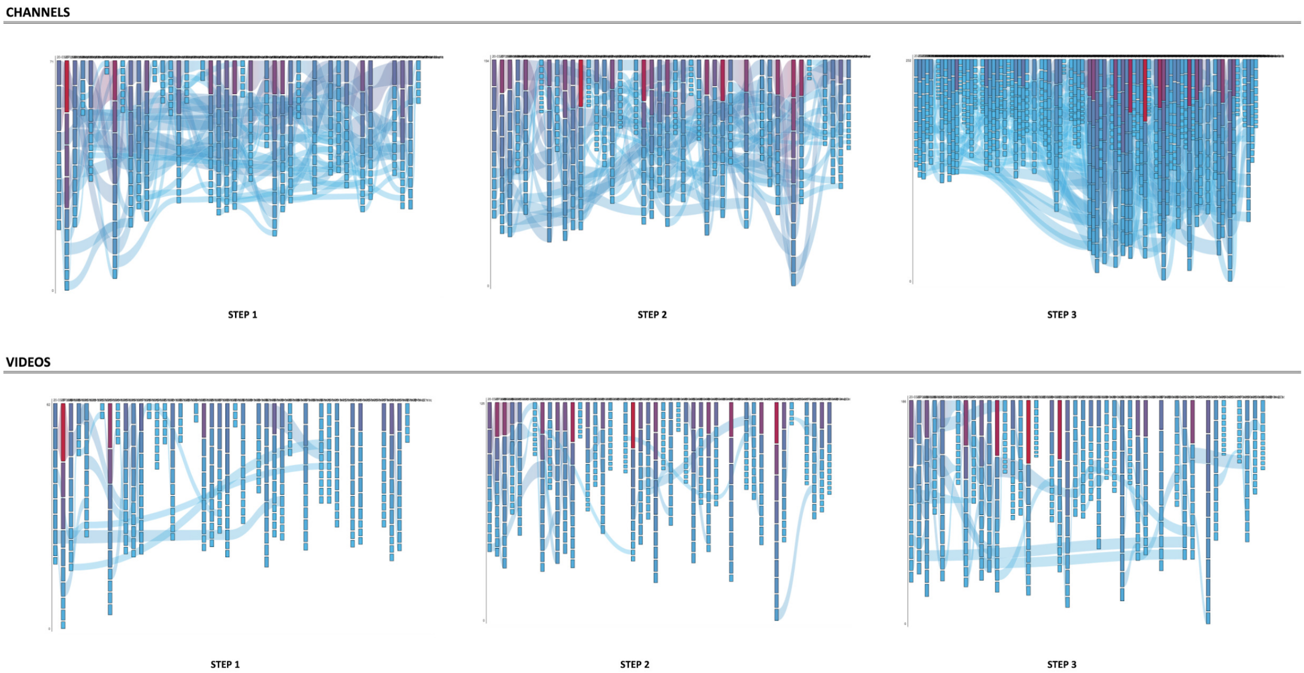

Figure 2. RankFlow visualization of "coronavirus" for the top 10 most frequently recommended channels at step 1, step 2, and step 3 (top), and for the top 10 most recommended videos at step 1, step 2, and step 3 (bottom). Notes: In the RankFlow charts, for all queries, columns represent days, and blocks individual videos or channels, ranked by number of recommendations, with the top-ranking video or channel on top of the column; color (blue to red) and bar height both indicate the number of times a channel or video was recommended on a single day; blue, purple, and red "waves" are created when the tool identifies that a particular video or channel appears on multiple days, that is, the tool creates a flow to trace the recurrence of unique videos or channels over time; morphologies with many "waves" (see channel rank flows, step 3) indicate the presence of certain videos and channels recurrently recommended over time.

Table 1). In terms of source diversity, US channels make up between 70% (n = 14) and 75% (n = 15) of the top 20 channels at each step, while UK channels make up between 10% (n = 2) and 15% (n = 3). Fox News, which has played an important role in spreading Covid-19 misinformation (Li et al., 2020), does progressively better as we go down the chain: ranking 17th at step 1, 10th at step 2, and 7th at step 3, being recommended over 6, 8, and 17 days, respectively.

The channels of health authorities such as the World Health Organization (WHO) and the Centers for Disease Control (CDC; both with "silver" status) were absent across all steps. This is despite the fact that on 2 April 2020, YouTube encouraged creators to base their coronavirus-related material on information from "reputable sources" such as WHO and CDC (YouTube Help, 2020) and that the WHO's channel was active over this time.

Turning to content diversity, a handful of videos from mainstream news channels "win" repeatedly at each step. These videos had millions of views (as of February 2021 when the analysis was undertaken), were all uploaded during our period of study, and most had charged, if not sensationalist titles. For example, in step 1, the most frequently recommended video came from Channel 4 News, with the title *Coronavirus Expert: 'War is an Appropriate Analogy'* (see Table 2). Although not featured in our "top five" list, a video uploaded by New Tang Dynasty—a problematic news channel published under the Epoch Media Group and accused of spreading misinformation (Zadrozny & Collins, 2019)—was recommended 12 times over two days at step 1, ranking sixth, with over 4 million views at the time of analysis. This video featured an interview with the discredited scientist behind the infamous "Plandemic" video, Judy Mikovits (Shepherd, 2020), in which she raised questions about the origin of Covid-19.

4.3. Feminism

For the keyword "feminism," we found that mainstream news media (Fox News; Channel 4 News), entertainment (The Late Late Show with James Corden), and educational channels (TEDx Talks and TED) falling predominantly within the "silver," "gold," and "diamond" tiers, were the clear "winners" across steps (see Table 3). As Figure 3 shows, YouTube offers more variance in how it recommends videos than it does channels for "feminism," but the difference is less pronounced than for "coronavirus." In step 1, only 11.9% of videos (n = 17) were recommended on two or more days during the period studied, whereas 23.8% of channels (n = 30) were recommended on more than one day.

Table 1. Top 20 channels recommended for "coronavirus" at each step.

Step 1	R	D	Step 2	R	D	Step 3	R	D
NBC News*	203	32	NBC News*	547	39	NBC News*	1030	39
Channel 4 News*	104	18	MSNBC*	234	26	MSNBC*	402	25
MSNBC*	89	18	Channel 4 News*	226	22	60 Minutes Australia*	299	19
BBC News*	70	20	CNN♦	149	16	Channel 4 News*	296	18
TODAY*	69	15	LastWeekTonight*	118	11	CNN♦	292	21
CNN♦	62	15	60 Minutes Australia*	112	15	LastWeekTonight*	237	11
DW News*	48	12	Global News*	107	14	Fox News*	212	17
60 Minutes Australia*	41	13	BBC News*	100	13	CNBC Television*	180	11
LastWeekTonight*	39	8	NewsNOW from FOX*	95	11	The Daily Show with Trevor Noah*	167	11
The Daily Show with Trevor Noah*	33	7	Fox News*	94	11	ABC News♦	136	10
ABC News♦	30	9	The Daily Show with Trevor Noah*	92	10	BBC News*	133	12
Global News*	29	10	TODAY*	91	12	Late Night with Seth Meyers*	132	11
NewsNOW from FOX*	28	6	DW News*	84	12	Global News*	128	10
Washington Post*	27	6	CNBC Television*	81	10	TODAY*	118	10
The Late Show with Stephen Colbert*	22	5	Fox Business*	65	8	NewsNOW from FOX*	111	9
The White House*	22	4	CBS News*	64	9	CBS News*	110	10
Fox News*	20	6	Late Night with Seth Meyers*	59	8	The Late Show with Stephen Colbert*	104	7
CBS News*	20	7	TIME*	51	7	CNBC*	83	6
Guardian News*	20	6	ABC News♦	49	8	Sky News*	80	5
CNBC Television*	19	6	Washington Post*	49	8	The White House*	73	7

Notes: Column "R" indicates the number of times the channel was recommended; column "D" indicates the number of days on which the channel was recommended more than once; symbols indicate channel subscription status—diamond symbol (♦) for "diamond" and asterisk (*) for "gold."

Regarding trends across the entire chain over time (see Table 3), TEDx Talks ("diamond" status) was the clear "winner" at each step, and PowerfulJRE (The Joe Rogan Experience podcast), which has courted controversy for being "a safe space to launder bad ideas" (Maiberg, 2018), was also prominent. Ranking 16th at step 1, *PowerfulJRE* ("diamond" status) goes on to rank second at both steps 2 and 3, outperforming mainstream news and entertainment channels. In terms of locales, US channels dominate, though to a lesser extent than they did for "coronavirus." At each step, US media sources make up between 50% (n = 10) and 60% (n = 12) of the top 20 channels. Indian channels also did well, making up between 15% (n = 3) and 30% (n = 6) of the top 20 channels at each step. This is likely related to a controversy involving Indian actress Neha Dhupia's comments about violence against women ("Neha Dhupia addresses," 2020). Among the Indian channels recommended across steps and over time (and which are distributed, roughly equally, across tiers ranging from "bronze" to "diamond"), those engaged in anti-feminist content (e.g., PeepOye Fame, Sahil Chhikara, Tanmay Bhat, and Bollywood Samachar) outperformed educational channels featuring videos on topics that include feminism (NPTEL-NOC IITM and UPSC Preparation). It is striking that none of the top 20 most recommended channels at each step self-describe as "feminist." The first self-described feminist channel to appear in our dataset is South-Korean 하말넘많 [heavytalker], which ranks 37th at step 2.

With regard to content diversity, looking at the top-recommended videos across steps, an anti-feminist trend was clear (see Table 4). Videos featuring the controversial public intellectual Jordan Peterson emerge as "winners." Following a Channel 4 News interview with Peterson which was recommended at step 1, a Joe Rogan interview with Peterson in which he criticizes the existence of "Women's Studies" departments at universities is the second most frequently recommended video at both steps 2 and 3, and a video of Peterson's 2018 book

Table 2. Top five videos recommended for "coronavirus" at each step.

Step	Video title	Channel	R	D
Step 1	Coronavirus Expert: "War is an Appropriate Analogy"	Channel 4 News	35	4
	Journalist Goes Undercover at "Wet Markets," Where the Coronavirus Started	60 Minutes Australia	31	8
	Coronavirus II: Last Week Tonight With John Oliver (HBO)	LastWeekTonight	17	3
	Coronavirus Disrupts Daily Life as Trump Declares National Emergency	TODAY	13	1
	Trump's Coronavirus Address, Blooper Reel Included	The Daily Show with Trevor Noah	12	3
Step 2	Coronavirus Expert: "War is an Appropriate Analogy"	Channel 4 News	67	4
	Watch CNBC's Full Interview With Berkshire Hathaway CEO Warren Buffett	CNBC Television	61	9
	Journalist Goes Undercover at "Wet Markets," Where the Coronavirus Started	60 Minutes Australia	61	7
	Trump's Coronavirus Address, Blooper Reel Included	The Daily Show with Trevor Noah	45	5
	Coronavirus: Last Week Tonight With John Oliver (HBO)	LastWeekTonight	44	5
Step 3	Journalist Goes Undercover at "Wet Markets," Where the Coronavirus Started	60 Minutes Australia	143	10
	Watch CNBC's Full Interview With Berkshire Hathaway CEO Warren Buffett	CNBC Television	134	10
	Coronavirus Wxpert: "War is an Appropriate Analogy"	Channel 4 News	96	5
	Coronavirus: Last Week Tonight With John Oliver (HBO)	LastWeekTonight	83	5
	Trump's Coronavirus Address, Blooper Reel Included	The Daily Show with Trevor Noah	59	5

Notes: Column "R" indicates the number of times the video was recommended; column "D" indicates the number of days on which the video was recommended more than once.

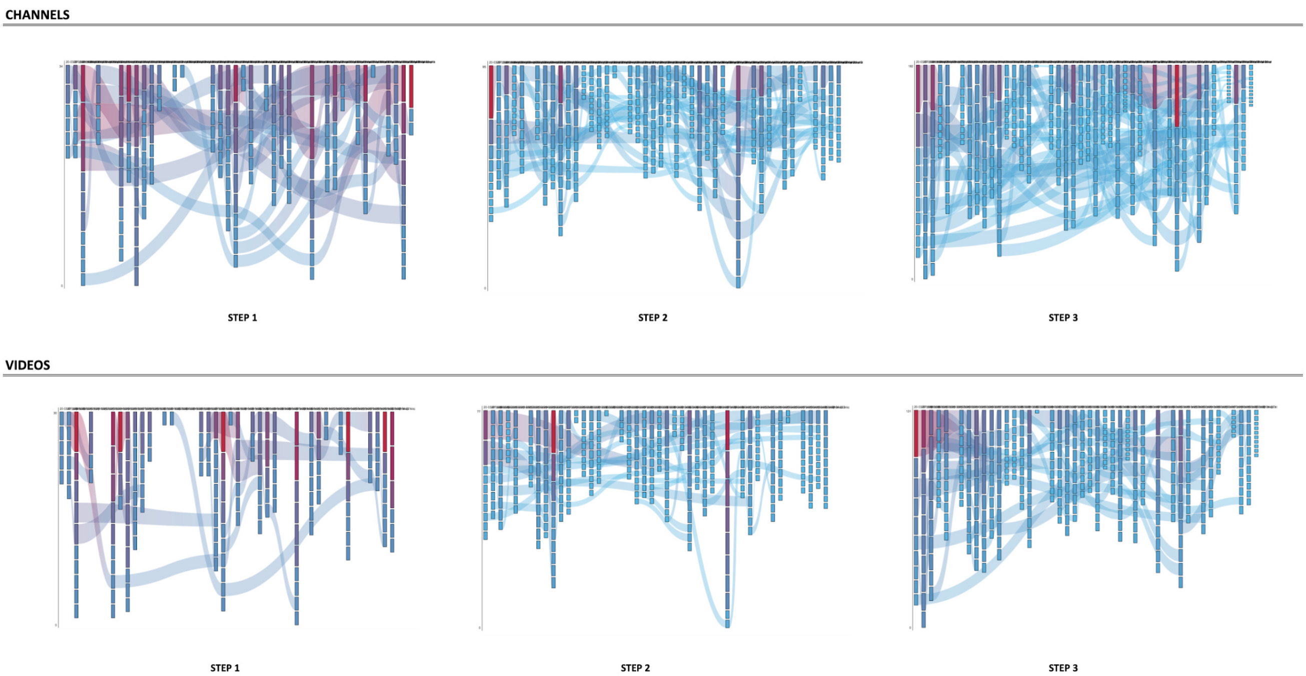

Figure 3. RankFlow visualization of "feminism" for the top 10 most recommended channels at step 1, step 2, and step 3 (top), and for the top 10 most recommended videos at step 1, step 2, and step 3 (bottom).

Table 3. Top 20 channels recommended for "feminism" at each step.

Step 1	R	D	Step 2	R	D	Step 3	R	D
TEDx Talks♦	76	22	TEDx Talks♦	198	27	TEDx Talks♦	696	30
The Late Late Show with James Corden♦	32	9	PowerfulJRE♦	56	14	PowerfulJRE♦	286	23
Fox News*	25	9	Channel 4 News*	48	13	SET India♦	116	7
TED♦	16	6	NBC News*	47	8	NBC News*	116	10
Channel 4 News*	16	6	PeepOye Fame♠	45	6	TED♦	111	12
PeepOye Fame♠	16	4	SET India♦	31	5	Fox News*	84	7
The University of Melbourne♣	13	4	TED♦	30	8	92nd Street Y♠	82	6
NewsNOW from FOX*	13	3	Tanmay Bhat*	28	4	Channel 4 News*	77	8
NPTEL-NOC IITM♠	9	3	Fox News*	26	5	Talent Replay*	76	5
NBC News*	9	3	TIME*	23	3	LastWeekTonight*	70	6
The White House*	9	2	How To Academy♠	22	5	Got Talent Global♦	64	5
Washington Post*	8	2	CBS News*	22	5	Top Viral Talent♦	62	5
Fox Business*	8	2	Fox Business*	22	4	PeepOye Fame♠	53	4
LastWeekTonight*	7	2	Bollywood Samachar*	19	4	Habertürk TV♠	52	5
SET India♦	7	2	LastWeekTonight*	16	3	TVO Docs♣	39	3
PowerfulJRE♦	7	2	Talent Replay*	15	2	How To Academy♠	38	5
UPSC Preparation♣	7	1	Sahil Chhikara♣	15	4	Top 10 Talent*	37	3
The Hill*	6	2	After Work Reactions♣	15	3	The Agenda with Steve Paikin♠	37	4
Ninja Nerd Science♠	6	3	Gauthali Entertainment♥	15	4	Tanmay Bhat*	34	3
Jordan B Peterson*	6	3	NPTEL-NOC IITM♠	14	3	After Work Reactions♣	33	3

Notes: Column "R" indicates the number of times the channel was recommended; column "D" indicates the number of days on which the channel was recommended more than once; symbols indicate channel subscription status—diamond symbol (♦) for "diamond," asterisk (*) for "gold," spades (♠) for "silver," clubs (♣) for "bronze," and hearts (♥) for "opal."

presentation is in the top five videos recommended at both steps 2 and 3. Beyond Peterson, there is a notable presence of videos from Indian channels that seem to mock or disparage Neha Dhupia (e.g., videos with titles such as *Destroying Pseudo Feminists Neha Dhupia and Nikhil Chinapa*).

Among the top five recommended videos for "feminism" at each step, only the videos related to the Neha Dhupia controversy were uploaded during our period of study. All remaining videos, some of which were unrelated to the topic of feminism, were uploaded to YouTube years beforehand. For example, a 2015 video on the health dangers of wireless radiation by Dr. Devra Davis (see Table 4), the appearance of which might be explained by activity around Covid-19 on YouTube at the time of data collection, including public discussions related to 5G conspiracy theories (Bruns et al., 2020).

4.4. Beauty

For "beauty," channels promoting DIY crafts and beauty hacks (5-Minute Craft, 5-Minute Crafts GIRLY, 123 GO!, and 5-Minute Crafts VS), falling within the "gold" and to a lesser extent "diamond" tiers, dominate the ranking of most recommended channels across steps (see Table 5). As observed for "coronavirus" and "feminism," as Figure 4 shows, we observed substantial content diversity, especially at step 1. While only 20% of videos (n = 17 videos) were recommended on two or more days in step 1 during the period studied, 31.4% of channels (n = 22) were recommended on more than one day.

Regarding trends across the entire chain over time (see Table 5), "5-minute" channels are the clear "winners" across steps, together accounting for between 40% (n = 8) and 45% (n = 9) of the top 20 channels at each step. These US-based channels pertain to TheSoul Publishing, an online publisher subject to claims of "gaming" YouTube's algorithm, including by uploading videos frequently and using clickbait strategies (Jennings, 2018). Similarly, Troom Troom, a channel of "mysterious international origin," which posts DIY/hack videos and takes an approach similar to that of the "5-minute" channels (Jennings, 2018), was recommended several times across different days in both step 2 and step 3.

In contrast to our findings for "coronavirus" and "feminism," mainstream news media channels are completely absent from our top 20 recommendations across steps for "beauty." Native-YouTube channels clearly dominate.

Table 4. Top five videos recommended for "feminism" at each step.

Step	Video title	Channel	R	D
Step 1	Pitch Perfect Riff-Off With Anna Kendrick & The Filharmonics	The Late Late Show with James Corden	22	7
	Meeting the Enemy: A Feminist Comes to Terms With the Men's Rights Movement | Cassie Jaye	TEDx Talks	19	8
	"The Truth About Mobile Phone and Wireless Radiation" —Dr. Devra Davis	The University of Melbourne	17	6
	Destroying Pseudo Feminists Neha Dhupia and Nikhil Chinapa (MTV Roadies Revolution) #AkasshReacts	Peepoye	16	4
	Jordan Peterson Debate on the Gender Pay Gap, Campus Protests and Postmodernism	Channel 4 News	13	5
Step 2	Destroying Pseudo Feminists Neha Dhupia and Nikhil Chinapa (MTV Roadies Revolution) #AkasshReacts	Peepoye	37	5
	Joe Rogan Experience #877 With Jordan Peterson	PowerfulJRE	25	9
	This Title is Her Choice—Roadies Cringe Mahotsav	Tanmay Bhat	24	4
	Jordan B. Peterson on 12 Rules for Life	How To Academy	24	6
	Bollywood Angry Reaction on Neha Dhupia Roadies Controversy@Bollywood Samachar	Bollywood Samachar	17	4
	Top 10 Funny Performances Got Talent	Talent Replay	98	8
Step 3	Joe Rogan Experience #877 With Jordan Peterson	PowerfulJRE	86	12
	Jordan B. Peterson on 12 Rules for Life	How To Academy	58	9
	How to Learn Any Language in Six Months | Chris Lonsdale	TEDx Talks	46	5
	The Mathematics of Weight Loss | Ruben Meerman | TEDxQUT (Edited Version)	TEDx Talks	45	4

Notes: Column "R" indicates the number of times the video was recommended; column "D" indicates the number of days on which the video was recommended more than once.

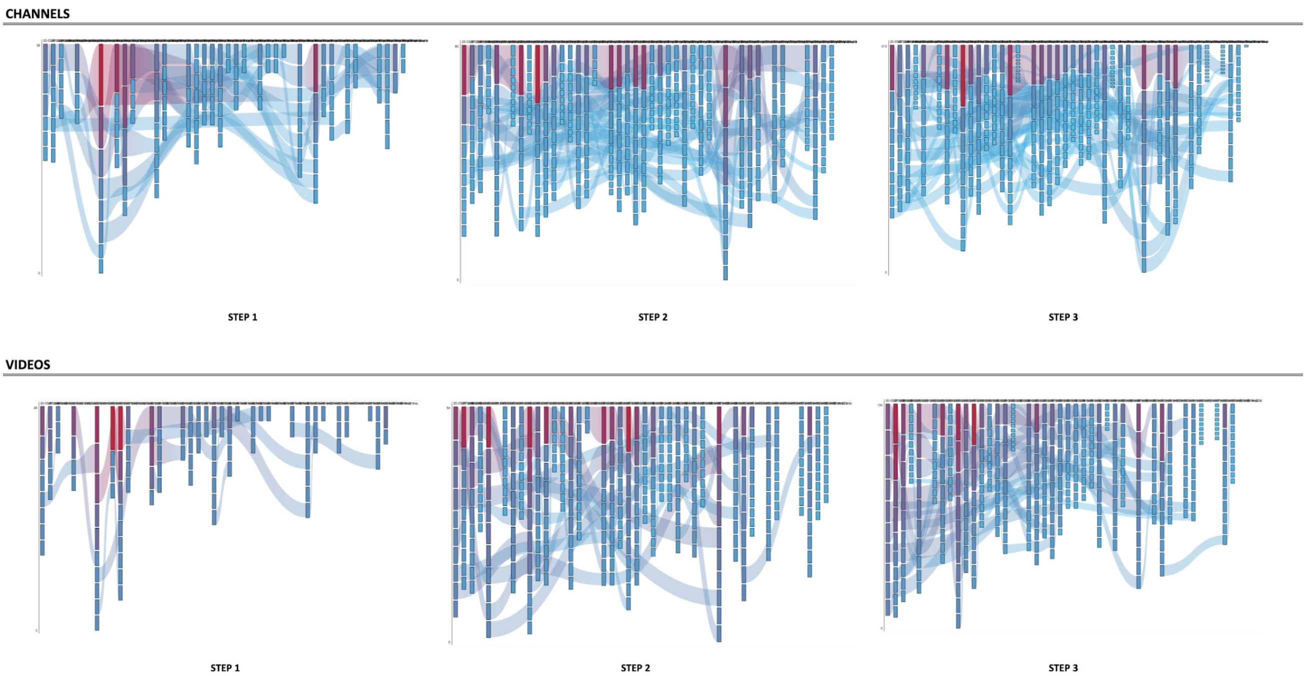

Figure 4. RankFlow visualization of "beauty" for the top 10 most recommended channels at step 1, step 2, and step 3 (top), and for the top 10 most recommended videos at step 1, step 2, and step 3 (bottom).

Table 5. Top 20 channels recommended for "beauty" at each step.

Step 1	R	D	Step 2	R	D	Step 3	R	D
5-Minute Crafts♦	79	23	5-Minute Crafts♦	316	33	5-Minute Crafts♦	923	33
5-Minute Crafts♦ GIRLY	39	15	5-Minute Crafts♦ GIRLY	87	17	5-Minute Crafts♦ GIRLY	188	15
Vogue*	21	6	5-Minute Crafts VS*	66	14	Vogue*	181	15
123 GO! *	19	5	Vogue*	48	8	5-MINUTEN-TRICKS*	130	8
5-Minute Crafts VS*	17	7	123 GO! *	43	7	5-Minute Crafts VS*	123	12
5-Minute Crafts FAMILY♦	17	8	5-Minute Crafts FAMILY♦	41	10	Dawn Gallagher♣	106	7
123 GO Like! *	12	5	123 GO! SCHOOL*	40	7	123 GO! SCHOOL*	93	8
Beauty Lady	11	5	5-MINUTEN-TRICKS*	35	7	Troom Troom♦	90	6
TIK TOK N SANAM♣	8	4	Dawn Gallagher♣	29	4	5-Minute Crafts FAMILY♦	75	7
Crafty Panda♦	7	3	123 GO Like! *	29	6	Jen Phelps♣	58	4
Dawn Gallagher♣	6	2	Troom Troom♦	26	3	123 GO Like! *	56	5
5-Minute Crafts PLAY♦	6	2	Crafty Panda♦	16	3	123 GO! *	50	5
5-Minute Crafts Tech*	6	3	DIY Unique Ideas	14	3	DIY Unique Ideas	43	4
123 GO! SCHOOL*	6	3	Kim Lianne*	13	3	Kim Lianne*	41	3
Crazy Shayna	6	3	Crazy Shayna	13	3	Jen Luvs Reviews♠	41	3
DIY Unique Ideas	5	2	Beauty's Big Sister♣	12	3	Allie Glines♠	39	3
Dominique Sachse*	4	2	Ali Andreea♠	11	3	MarionCameleon♠	37	3
Kim Lianne*	4	2	Jessica Braun♠	11	2	TEDx Talks♦	32	3
RosyMcMichael*	4	2	Zachary Michael♠	11	2	Kelly Strack♠	32	3
Cassandra Bankson*	4	2	Yasmina Filali♣	10	2	Julia Mazzucato♣	32	2

Notes: Column "R" indicates the number of times the channel was recommended; column "D" indicates the number of days on which the channel was recommended more than once; symbols indicate channel subscription status—diamond symbol (♦) for "diamond," asterisk (*) for "gold," spades (♠) for "silver," and clubs (♣) for "bronze"; for channels without specified subscription figures, rows were left with no symbol.

There is a strong commercial element to many of the top-recommended channels for "beauty," for example, many YouTubers test and review products. US-based channels continue to feature prominently: between 60% (n = 12) and 75% (n = 15) of the top 20 channels at each step are US-based. Regarding popularity, between 75% (n = 15) and 80% (n = 16) of the top 20 channels at each step fall within the "silver," "gold," or "diamond" tiers.

Turning to videos, a video from 5-Minute Crafts, offering up "cooking tricks," is the clear recommendation winner across steps and, in general, TheSoul Publishing's "5-Minute' channels" videos occurred most frequently (see Table 6). The only other videos in the top five were uploaded by Vogue and American beauty expert Dawn Gallagher. Notably, all the recurring videos from TheSoul Publishing's "5-minute" channels used fully capitalized letters (e.g., "33 GIRLY HACKS YOU DIDN'T KNOW BEFORE"), exemplifying the use of clickbait tactics to "game" the YouTube algorithm (Jennings, 2018). In terms of a diversity of viewpoints and representation, the top-recommended videos offer a commercialized and gendered representation of beauty and a limited representation of people of color.

5. Discussion

Our investigation shows significant variation in recommended videos (content diversity) over time and across queries, especially at step 1. This finding aligns with the company's longstanding commitment to "diversification" in the "up next" section (Davidson et al., 2010; The YouTube Team, 2019a). Yet, YouTube's operationalization of media diversity deserves further attention. First, we found that the platform clearly prioritizes certain channels (source diversity) over time and across steps, which provided important insights into how YouTube operationalizes "authoritativeness" in practice. US channels dominated across queries, down the chains, and over time, which highlights the cultural dominance of the US on YouTube (Rieder et al., 2020). From our data, it also seems clear that YouTube, following political and social pressure, makes decisions to categorize certain topics societally significant and truth-oriented enough for heavy-headed platform intervention (e.g., vaccination, climate change, elections), while others (e.g., gender, politics, and beauty) are considered less so. For "coronavirus," for example, YouTube amplified US news partners in the chain. Users' location

Table 6. Top five videos recommended for "beauty" at each step.

Step	Video title	Channel	R	D
Step 1	100 Cooking Tricks That Will Help You to Cut Costs || Live	5-Minute Crafts	16	6
	Hilary Duff's Busy Mom Makeup Routine | Beauty Secrets | Vogue	Vogue	14	4
	33 Girly Hacks You Didn't Know Before	5-Minute Crafts VS	10	4
	17 Genius Ideas for Girls || Hair and Makeup Transformations	5-Minute Crafts	9	2
	31 Colorful Hair Hacks for a Flawless Look	5-Minute Crafts GIRLY	9	4
Step 2	100 Cooking Tricks That Will Help You to Cut Costs || Live	5-Minute Crafts	90	19
	101 Easy Yet Genius Kitchen Hacks You've Never Seen Before	5-Minute Crafts	49	10
	Makeup Techniques for Women Over 40! Dawn and Joseph	Dawn Gallagher	29	5
	100 Best Cooking Hacks Live	5-Minute Crafts	23	8
	33 Girly Hacks You Didn't Know Before	5-Minute Crafts VS	21	5
Step 3	100 Cooking Tricks That Will Help You to Cut Costs || Live	5-Minute Crafts	234	22
	100 Best Cooking Hacks Live	5-Minute Crafts	164	18
	Makeup Techniques for Women Over 40! Dawn and Joseph	Dawn Gallagher	105	8
	All-Time Best Life Hacks Everyone Should Know	5-Minute Crafts	93	12
	100 Best Kitchen Tips || Cooking Hacks, Easy Recipes and Yummy Ideas	5-Minute Crafts	79	8

Notes: Column "R" indicates the number of times the video was recommended; column "D" indicates the number of days on which the video was recommended more than once.

information, though, influences the news channels surfaced by YouTube, as the appearance of Australian news channels (e.g., 60 Minutes Australia) in our data demonstrates. This is in line with YouTube's announcement that it was surfacing local trusted news outlets for newsworthy events (Mohan & Kyncl, 2018). For "feminism" and "beauty," in contrast, YouTube-native anti-feminist content creators (e.g., PeepOye Fame; Sahil Chhikara), and "5-Minute" channels, respectively, dominated the "up next" section over time and across steps, raising the question of how easily channels operated by "entrepreneurs" and powerful publishing companies can become "authoritative voices" on topics with clear consumer and niche markets.

When moderating at the level of the channel, YouTube has had some success: YouTube-native niche entrepreneurs promoting conspiracy theories have reportedly experienced a drop in views since the platform updated its systems to demote borderline content (Thomson, 2020). However, our findings reveal the problems associated with prioritizing content from news partners (and from users that self-certify as verified accounts) as an approach to operationalizing the promotion of authoritative content (Caplan, 2020), especially when channels such as Fox News have been known to circulate misinformation, channels including PowerfulJRE are known for laundering "bad ideas" (Maiberg, 2018) and 5-minutes Crafts channels engage in clickbait practices (Jennings, 2018).

Second, while YouTube might be committed to offering video diversity in the "up next" section, we found that the videos most recommended for each of our queries did not feature a breadth of genres, viewpoints, or framings. For "beauty," YouTube's "up next" section favored channels that upload highly stereotyped, commercialized, and gendered content, and for "feminism" it prioritized channels run by male YouTubers with strong anti-feminist views. We consider these findings to indicate YouTube has not effectively addressed content diversity from a social perspective (failing to attend to factors such as race, gender, nationality, sexuality, and ability).

Our findings also indicate a clear correlation between frequently recommended videos and channels, and popularity and "freshness" (proxies for "quality"). All the channels that were "winners" in the recommendation chain across queries fell predominantly within the "silver,'' "gold," and "diamond" tiers, which means that these media sources are part of an "elite" group representing less than 1% of all YouTube channels (Rieder et al., 2020). For videos, almost all of the most frequently recommended videos had accrued millions of views. The recency signal was also evident in our data: The most frequently recommended channels were uploading videos regularly during the period of our data collection, and most frequently recommended videos were often recently uploaded. However, we also found older "viral" videos repeatedly recommended, some of which were potentially problematic in terms of misinformation, especially for "coronavirus" and "feminism."

Recency and popularity alone, though, are insufficient to explain why certain problematic videos and less popular channels appear in the "up next" recommendation chain. Platform and issue vernaculars also play a part. Content creators are increasingly aware of the importance of gaming social media algorithms to boost visibility (Bishop, 2019), and they implement and test various optimization tactics—e.g., use of relevant keywords in headlines—to increase their chances of being amplified by YouTube's recommendations systems, which was visible in both "feminism" and "beauty." Optimization tactics might explain the appearance of some channels with "opal" and "bronze" status—so-called micro-influencers (Boerman, 2020)—within the top 20 most recommended channels for "beauty," such as former model Dawn Gallagher and beauty and fashion YouTuber Julia Mazzucato.

For "feminism," audience viewing patterns and the "data void" problem (Golebiewski & boyd, 2019) might explain the overrepresentation of anti-feminist YouTube content creators around discussions of "feminism" (Döring & Mohseni, 2019). Arguably, YouTube has a much richer repository of content in the case of "coronavirus" and "beauty" than it does for "feminism," which might result in recommendations of less popular and/or less relevant content for that search term. Data voids are especially concerning when they have been successfully exploited by actors pushing problematic agendas, such as those that are anti-feminist or misogynistic. Although YouTube was alerted to this issue in 2015 (Golebiewski & boyd, 2019, p. 29), and despite highly popular feminist YouTubers being active on the platform (e.g., Jouelzy, Feminist Frequency), our study indicates that five years later, it is still a problem.

Last, our analysis shows that the algorithms underpinning the "up next" feature, as with ranking, are sensitive to newsworthy events and controversies (Rieder et al., 2018, p. 63). This was visible in the "feminism" data where India-based channels that had uploaded new content to YouTube were recommended at high rates after a gender-based controversy relating to actress Neha Dhuphia. Sensitivity to current events shows the importance of studying YouTube's "related videos" algorithm over time and as part of the broader media system in which YouTube exists, where different internal and external agencies converge to influence how the platform recommends content to users.

6. Conclusion

This article has provided new evidence about what the algorithms underpinning YouTube's "up next" feature "do" over time, down the recommendation chain, and in relation to specific issue spaces. We paid attention to YouTube's "moments of choice" that find their form in algorithmic processes (e.g., a commitment to content diversity and to the promotion of authoritative voices) and the impact of platform and issue vernaculars on what content gets surfaced in the "up next" section, albeit without fully accounting for the effects of personalization. Critically, we have also shown how corporate understandings of "diversity," "quality," and "authoritativeness," and their operationalization in practice, can have significant limitations in terms of improving the types of content that are amplified by automated recommendations systems and, potentially, the type of information users are exposed to in relation to certain issue domains. For future research, our approach to "platform observability" (Rieder & Hofmann, 2020, p. 21) might be usefully combined with studies that build on issue comparisons while also accounting for personalization.

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Conflict of Interests

The authors declare no conflict of interests.

Supplementary Material

Supplementary material for this article is available online in the format provided by the author (unedited).

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