YouTube Recommendations and Effects on Sharing Across Online Social Platforms

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YouTube recently announced a decision to exclude potentially harmful content from video recommendations while allowing such videos to remain on the platform, but it is unclear whether this compromise is sufficient in mitigating YouTube’s role in propagating this content. To assess this impact, we measure YouTube sharing in Twitter and Reddit in the eight months around YouTube’s announcement using interrupted time series models. These models evaluate YouTube’s impact on sharing of videos from a curated set of alternative political channels and popular videos shared in three conspiracy-oriented Reddit subreddits; we compare these models to a placebo dataset of makeup-oriented videos that should be unaffected by YouTube’s announcement. Results suggest YouTube’s de-recommending AIN-produced content has a significant suppressive effect on sharing of AIN videos in both Twitter and Reddit, with our models showing a significant and downward trend in sharing. For conspiracy video sharing, however, we see no significant change in Reddit and find an increase in the level of conspiracy sharing in Twitter. We see no significant effect on makeup sharing in either platform, suggesting YouTube’s targeting particular content types has a targeted effect. Reducing exposure to anti-social videos without deleting them therefore has the potential to improve quality across the information ecosystem, but additional transparency is needed to evaluate these effects further.

CCS Concepts: • Human-centered computing → Empirical studies in HCI; Social media; • Networks → Social media networks; • Social and professional topics → Computing / technology policy.

Additional Key Words and Phrases: youtube; twitter; reddit; content quality; moderation; cross-platform

1 INTRODUCTION

On 25 January 2019, YouTube announced an initiative to improve the quality of content on its platform and the content the platform recommends to its users [22]. In this new effort, YouTube claims to use a combination of machine learning and human evaluation to identify videos “that could misinform users in harmful ways” and videos that present “borderline content”; these videos are then removed from recommendation (e.g., they are excluded from the “Recommended” section on users’ homepages and the ”Up Next” scroll after videos) [22]. This new approach may impact the larger information ecosystem, as recent work by Ribeiro et al. [14] and editorials [19] have suggested YouTube’s recommendation systems can radicalize individuals. Therefore, by reducing exposure to such content, YouTube’s actions may have a positive effect in online information quality.

At the same time, YouTube is one of the largest online platforms globally, with YouTube content routinely being some of the most shared across Twitter and Reddit. This popularity may render YouTube’s new content moderation policy ineffective if many individuals are finding this content through social interactions on other platforms. Focusing only on effects within YouTube then omits critical aspects of its role in propagating content “that could misinform users in harmful ways” [22].

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To understand how YouTube’s recommendation leads to the propagation of misinformation, we need to examine how those YouTube videos are shared across other social media platforms. As YouTube is not the only platform dealing with such issues, this announcement provides a unique opportunity to evaluate a modulated content moderation strategy beyond the boundaries of a single platform. We are then left with the following question: Does YouTube’s action have a significant impact on sharing patterns of a subset of harmful and misinforming YouTube videos on other online social networking platforms?

We divide this question across two axes: the online social platform and the type of video. At the platform level, we examine whether YouTube’s change has impacted sharing on Twitter and on Reddit. At the video level, because YouTube does not publish or identify videos it has flagged as potentially misinforming or harmful, we cannot directly examine impact on these “potentially harmful” videos. Instead, we must identify proxies for classes of videos that may overlap with YouTube’s target videos. We therefore test whether YouTube’s change affect sharing of potentially harmful videos by comparing three different themes of YouTube videos that may be affected by this change in varying degrees:

**AIN Videos** Our first test set is composed of politically extreme videos constructed from a curated collection of “alternative” YouTube channels identified as part of the “Alternative Influence Network” (AIN) in recent work by Lewis [8]. These AIN channels provide “an alternative media source for viewers to obtain news and political commentary” that “facilitates radicalization” [8] and therefore appear to satisfy YouTube’s definition of misinforming/harmful content (though we acknowledge no publicly available mechanism exists to identify definitively what videos YouTube has labeled). Recent work has also shown evidence that YouTube’s recommendation system has had a significant effect on the sharing of these AIN-sourced videos within YouTube [18].

**Conspiracy Videos** Our second set of videos is composed of general conspiracies, as distinct from the set of AIN videos (with a Jaccard similarity of 0.002864%). These videos are not necessarily political in nature but may still misinform or lead to real-world conflict (as demonstrated with fake news-inspired violence in India [10]) and include videos about anti-vaccination, the Illuminati, moon landing conspiracies, and other similar conspiratorial content. Our motivation for testing videos these conspiracy videos is two-fold: 1) Research shows conspiracy-focused content may promote alternative narratives that result in harm and “create or fuel violence” [17], and 2) Media reports on YouTube’s efforts have also characterized this change as targeting “conspiracy” videos (e.g., Wakabayashi, 2009 [21]), though YouTube has not explicitly referred to the targeted content using that label.

**Makeup Videos** Our third set is comprised of makeup-related videos, which unlike AIN and conspiracy videos, we expect should be largely unaffected by YouTube’s changes to its recommendation system. As this set has no videos in common with the AIN and conspiracy video sets, we use these makeup videos as a control and placebo test.

To evaluate the impact of YouTube’s action on these platforms and video types, we compare sharing frequencies before and after YouTube’s announcement using a form of interrupted time series (ITS) analysis. ITS analysis has been similarly been used to assess the impact of other content moderation policies, as in Reddit’s banning of several anti-social communities in 2015, as described in Chandrasekharan et al. [3].

Our results suggest YouTube’s de-recommending AIN-produced content has a significant effect on sharing of AIN videos in both Twitter and Reddit, with our models showing a significant and downward trend in spread on both platforms. For conspiracy video sharing, however, we see no significant change in Reddit but find an increase in the level of conspiracy sharing in Twitter. Effects
on makeup sharing are as we anticipated, as we see no significant change in sharing on either platform. We note that, while we examine only a strict subset of all possible “potentially harmful and misinforming” videos that may exist on YouTube’s platform, the analysis reveals that YouTube’s efforts do have a potentially normative effect on sharing across platforms for a particular type of video that prior evidence suggests have been impacted by YouTube’s modification. Numerous other types of potentially harmful videos exist (e.g., hate, racism, sexism, “fake news”, etc.), and how these videos are impacted by YouTube’s moderation efforts are open questions we leave for future work.

We conclude by reflecting on potential confounders in assessing the impact of YouTube’s announcement and the apparent normative effects it had on AIN sharing versus the inconsistencies in conspiracy-video sharing. We compare these normative effects with the potentially unintended consequences of amplifying borderline content that may fill the vacuum in recommendations left by removing more clearly harmful content. It is valuable to note that the impact of YouTube’s change on AIN videos is consistent in both Twitter and Reddit, increasing the validity of results in this work; though again, it is difficult to attribute these changes to YouTube’s algorithmic modifications and not other factors.

2 BACKGROUND

YouTube’s effort is part of a larger set of endeavors by Google, Facebook, and other companies to address radical and extremist content on their platforms. Such attempts have been controversial as opponents to these efforts claim the platforms are censoring their users and violating free speech. A point stressed in YouTube’s announcement, potentially in response to these claims, is that their change “will only affect recommendations of what videos to watch, not whether a video is available on YouTube” [22]. This move can then be viewed as a compromise, still allowing potentially fringe ideas a platform but without actively spreading these ideas through recommendations. Less diplomatic efforts, however, have had normative effects: Reddit went through a similar cycle of controversy with their outright banning of several hateful communities in 2015, and while contentious, research has since shown this ban had a socially normative effect on discourse within Reddit [3].

YouTube’s compromise in allowing these potentially misinforming/harmful videos to remain available has important implications since YouTube is not an isolated platform; rather, it exists within a broader information ecosystem. This ecosystem is comprised of numerous online information sources, from video platforms (e.g., YouTube and Twitch) to social media platforms (e.g., Facebook, Instagram, Twitter, and Reddit) to point-to-point messaging apps (e.g., WhatsApp or WeChat) to online news websites (e.g., the New York Times or Wall Street Journal’s websites or Internet-native news like BuzzFeed) and blogs (e.g., Tumblr, WordPress, etc.). As the median American uses three separate social media platforms [15], limiting exposure on a single platform (even one as large as YouTube) may have little effect on this content’s uptake, especially if the primary avenue for individuals to find this content is via other platforms. If a conspiracy-focused community on Reddit, Twitter, or Facebook is creating and sharing conspiracy-focused YouTube videos in these other spaces, such videos may still propagate rapidly across the information ecosystem regardless of whether they are being recommended natively within YouTube.

The power of these fringe communities in sharing anti-social content is already well-supported in the literature [9, 24], showing “tight-knit communities” in Reddit and other platforms spread content across the information ecosystem. Since YouTube is consistently one of the most popular platforms globally and one of the most popular domains linked to in Twitter and Reddit, the spread of these videos therefore may not rely on YouTube at all. Individuals’ primary vector for exposure to this content may instead be through interactions with other conspiracy-minded people rather than
YouTube’s on-site recommendation system. Alternatively, YouTube’s recommendation algorithm may be the primary vector through which otherwise unexposed individuals are shown this content (some work suggests this YouTube-specific radicalization pathway exists [14, 19]), and protecting individuals natively within YouTube could be an effective means to reduce exposure.

We are then left with a critical question: Does YouTube’s choice to modify its internal recommendations without actually deleting this content significantly impact the propagation of this content across the information ecosystem? If so, the financial incentive to produce this content may be reduced through smaller audiences, but if not, YouTube may need to take bolder steps to mitigate its role in the propagation of harmful content online. This question also has broader implications in how we should craft solutions for improving the information space: Are the actions of a single entity sufficient in this highly interconnected environment, or must the platforms work together to address these concerns? YouTube’s decision to stop recommending this content gives use a unique opportunity to explore this interconnection, and this paper presents a unique analysis of these interactions across millions of social media posts and videos.

2.1 Prior Work in Online Content Moderation

Content moderation in online social platforms is a well-studied problem, with most research existing on a spectrum between user perceptions of the moderation process (e.g., Myers West [12]) to analyses of the moderation strategy’s efficacy (e.g., Chandrasekharan et al. [3] and Chancellor et al. [2]), with hybrid approaches in between (e.g., Newell et al. [13]). This paper fits in the latter part of this spectrum, specifically exploring how YouTube’s announcement and ensuing action have impacted the spread of potentially harmful content beyond YouTube’s boundaries. The majority of similar work that studies the impact of moderation does so by identifying when a new moderation policy went into effect on a given platform and evaluating changes in user behavior or sharing within that same platform. While that approach has led to important findings, such as banning communities in Reddit increasing overall platform quality [3], or that users often find ways around content-based moderation strategies [2], it is difficult to apply to content creation platforms that do not directly support in-platform sharing, like YouTube. YouTube sharing, on the other hand, is intrinsically cross-platform, with the YouTube sharing button providing options for sharing to other platforms, like Twitter, Reddit, Facebook, etc. As a result, applying similar strategies to evaluate YouTube moderation are difficult since evaluation must necessarily use observations from other platforms. Therefore, an important novelty of this paper is its use of cross-platform data to evaluate the impact of YouTube’s moderation.

Of the prior work, Chandrasekharan et al. is most similar to our research [3]. In that effort, the researchers have used a similar ITS construct to evaluate changes to both discussion and user populations of communities within Reddit after Reddit banned several hateful and harassing communities. While our work is differentiated by platform and our cross-platform context, Chandrasekharan et al. is particularly germane as one could imagine Reddit as a microcosm of the internet, with interconnected but separate online spaces analogized by Reddit’s subreddit structure. In this analogy, a change to one subreddit’s moderation then indirectly impacts other subreddits through changes in population, cross-posting behavior, and language. In fact, Reddit has taken similar steps to YouTube’s de-recommendation by quarantining specific communities Reddit moderators have deemed to be in violation of their terms of service, as they did with the popular but controversial far-right subreddit /r/the_donald, a step that prevents content in that community from appearing on Reddit’s front page [20]. Likewise, Facebook and WhatsApp have taken similar steps to suppress the spread of problematic content by preventing WhatsApp users from broadcasting a link more than five times [4]. Both Reddit and Facebook’s steps are similar to YouTube’s efforts in that individuals are not banned from communicating their views, but the
platforms take steps to limit exposure of those views. As such, applying a study similar to Chandrasekharan et al. to investigate YouTube’s moderation approach, as we do here, has important implications beyond YouTube.

3 DATASETS
To compare YouTube sharing before and after YouTube’s announcement to de-recommend misin- forming and otherwise harmful videos, we use social media content collected from Twitter and Reddit. From this data, we extract links to YouTube videos to estimate daily sharing rates before and after this announcement. For Twitter, we leverage an archive of tweets collected from Twitter’s public sample stream, starting on 1 October 2018 and going until 31 May 2019 (representing four months on either side of YouTube’s change). This dataset contains 827,334,770 tweets. Studies on this data source have identified shortcomings in its use for tracking topical coverage over time [11], but it should be sufficient for gauging changes in popularity of individual links, as suggested in the stream mining chapter of Leskovec et al. [7]. We similarly collect Reddit submissions using PushShift.io’s collection during the same timeframe, resulting in 78,972,984 submissions. Our focus is only on submissions, excluding Reddit comments, as submissions are more comparable to tweets in length and modality.

We cannot directly search for links to YouTube within these datasets as link shorteners (e.g., bit.ly or TinyURL) obfuscate the terminal destination of a shortened link. Such shorteners are often used in social media data, accounting for 5% of links in our Twitter data and 0.03% of links in our Reddit data. After applying the urlexpander package\(^1\) to unshorten these links, we extract links to YouTube using the youtube-data-api package,\(^2\) as it captures both standard links to YouTube.com as well as shortened YouTube links (e.g., youtu.be) and embedded YouTube links. The resulting dataset contains 3,658,455 and 4,363,124 links to YouTube on Twitter and Reddit respectively. The youtube-data-api package also extracts YouTube video IDs from these links, yielding 3,273,473 and 3,641,872 unique YouTube videos on Twitter and Reddit. Of these videos, 284,875 appear in both platforms, resulting in a total of 6,630,470 YouTube videos.

3.1 Identifying Potentially Harmful YouTube Videos
We are particularly interested in whether YouTube’s change affects the prevalence of anti-social content in other platforms. While others have showed YouTube’s move to restrict recommendations of conspiracy and borderline content have impacted how often these videos are recommended within YouTube [18], we do not actually know to what videos YouTube’s restriction applies. Neither the automated classification scheme or human moderation codebook have been made publicly available by YouTube, and no video metadata appears to be available in YouTube’s APIs that would suggest whether a video is being or has been removed from recommendation. As a result, we lack a YouTube-native method to identify videos that have been flagged for removal from recommendation, meaning we cannot directly test whether these same videos are shared less on other platforms. In this exploration, we therefore study two sets of videos that may be restricted in YouTube, AIN-authored videos and videos popular in conspiracy communities, and compare these sets to a third potentially unaffected set of videos focusing on makeup and beauty care.

**AIN Videos**: An obvious source of such videos is captured by the channels participating in the AIN identified by Lewis [8]. As mentioned, AIN channels provide “an alternative media source for viewers to obtain news and political commentary” that “facilitates radicalization” [8], suggesting videos

\(^1\)https://github.com/smAPPNYU/urlexpander
\(^2\)https://github.com/smAPPNYU/youtube-data-api
posted by these channels are good candidates for potentially misinforming or harmful content. As shown by Suzor, videos posted to these channels experienced a steep decline in recommendation in February 2019 [18], suggesting these videos do overlap with YouTube’s classification scheme. Using these AIN channels as a source, we have identified 40,764 unique video IDs from 69 channels using YouTube’s API. These videos comprise our AIN video set.

Conspiracy Videos: While AIN channels are one type of potentially harmful content, other forms are popular on YouTube as well, ranging from anti-vaccine content to extraterrestrials, the Illuminati, and other topics. Many of these topics fall under the umbrella of conspiracy, pushing a narrative that explains some event through the actions of a relatively small group of conspirators, acting in secret [5, 6]. As noted in Sunstein and Vermeule, conspiracy theories can lead to conflict and violence [17] and potential public health crises, as seen with the Anti-Vax movement. Consequently, videos pushing conspiracy theories may also be targeted by YouTube’s actions, and the mainstream media has since labeled YouTube’s efforts as explicitly targeting such conspiratorial content [21]. We therefore construct a sample of conspiracy videos as a second class of a videos to evaluate.

Unfortunately, no existing dataset of conspiracy-oriented YouTube videos is publicly available, so we turn to a distant labeling mechanism to construct this dataset. Specifically, we identify YouTube videos shared on three conspiracy-focused Reddit communities between 1 January 2018 and 31 May 2019: /r/conspiracy, /r/conspiracy_commons, and /r/conspiracyfact. From these communities, we select videos whose Reddit “karma”, or popularity score, is in the top quartile of popularity. This selection process ensures we acquire videos that these conspiracy-focused communities have decided fit well within community norms, thereby removing conspiracy-debunking and spam videos. Table 1 shows these Reddit communities and the number of videos we selected from each one. Across these communities, we extract 2,070 unique video IDs, of which only 45 overlap with the AIN dataset described.

| Subreddit               | Videos |
|-------------------------|--------|
| /r/conspiracy           | 1,983  |
| /r/conspiracy_commons   | 139    |
| /r/conspiracyfact       | 46     |

A hand-labeled validation of 30 of these Reddit-sampled YouTube videos suggests 73% advance a specific conspiracy with 27% that are not specifically pushing a conspiracy theory but are related. This related class demonstrates the difficulty in identifying conspiracy content as well, as one such video (video ID M08WxAUQ4A) is an excerpt from the Golden Globes Awards in which the show hosts refer to vaccinations. This video has been posted in several anti-vaccination-oriented online communities.

While YouTube does not publicly identify de-recommended videos, it does provide additional contextual information for certain types of content. Specifically, videos about certain topics or that have received a significant amount of negative user feedback get flagged with additional metadata. One such example is the “clarification” flag, wherein YouTube attaches a text box below the video providing context and links to additional resources. Looking across the dataset, 158 are flagged in YouTube as in need of this clarification. Additionally, 6 videos are listed as having limited capabilities (i.e., YouTube has deactivated certain functionality related to the video because of

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3A selection of these channels have already been deleted by YouTube.
user complaints). While videos in need of clarification are not necessarily themselves conspiracies (videos that debunk conspiracies or videos about topics that often have conspiracies associated, like the Apollo 11 moon landings or the MH117 crash, also have this context box), this clarification flag does reveal that a non-trivial portion of the videos are related to conspiracy content. A further 294 videos result in an error on YouTube’s platform.

3.2 Building a Control Set of YouTube Videos

While the above collections are intended to capture videos that have been removed from recommendation by YouTube, we also construct a dataset of videos that are not subject to this removal as a placebo dataset to evaluate whether the effects we are capturing are specific to the video types of interest. To this end, we have selected makeup-related videos as a theme for building this dataset. Our motivation for this theme stems from the “Reddit’s 2019 Year in Review” blog post wherein makeup and beauty care were some of the most popular topics, and the post specifically lists Reddit’s top five makeup communities: r/makeupaddiction, r/muacjdiscussion, r/muacirclejerk, r/makeupexchange, and r/panporn. Using the same process as described for conspiracy videos, we have collected Reddit submissions that link to YouTube videos from these five communities. This collection has resulted in 774 unique YouTube video IDs distributed across three of the five communities, as shown in Table 2.

Table 2. Reddit’s top five makeup-related subreddits and videos shared therein. The subreddit r/makeupaddiction provides the most videos.

| Subreddit                  | Videos |
|---------------------------|--------|
| r/makeupaddiction         | 746    |
| r/muacjdiscussion         | 0      |
| r/muacirclejerk           | 28     |
| r/makeupexchange          | 0      |
| r/panporn                 | 11     |

To ensure our placebo dataset is sufficiently separate from our test datasets, Table 3 shows the overlap among all three video types. As the table illustrates, the makeup video set share nothing in common with either the AIN or conspiracy sets.

Table 3. Overlap in YouTube Video Sets. Each cell represents the number of videos in common between the video set in the column and row. Each video set is strongly distinct from the others, with the makeup video set having no videos in common with either of the other sets, making it a good candidate as a placebo test.

|                       | AIN Videos | Conspiracy Videos | Makeup Videos |
|-----------------------|------------|-------------------|---------------|
| AIN Videos            | 40,764     | 45                | 0             |
| Conspiracy Videos     | 45         | 2,070             | 0             |
| Makeup Videos         | 0          | 0                 | 774           |

4 DESCRIPTIVE STATISTICS

To evaluate the impact YouTube’s change to its recommendation system has had on Twitter and Reddit, we first calculate the daily tweets on Twitter and submissions on Reddit, which we collectively refer to as “posts”. We further extract the daily number of posts containing 1) links to
YouTube videos, 2) links to AIN-produced videos, 3) links to Reddit-sourced conspiracy videos, and 4) links to Reddit-sourced makeup videos. Time series for each of these video types divide into two regimes: pre- and post-YouTube’s announcement, or 1 October 2018 to 24 January 2019 (inclusive) and 25 January 2019 to 31 May 2019. We maintain time series data for each platform and sharing type and collect data on post frequencies to both platforms: \( n_{p,t} \) captures the number of messages posted to platform \( p \in \{ T, R \} \) for Twitter or Reddit respectively on day \( t \). We also capture \( v_{p,t}, a_{p,t}, c_{p,t}, \) and \( m_{p,t} \) as the number of links to YouTube videos \( v \), AIN-authored videos \( a \), conspiracy videos \( c \), and makeup videos \( m \) on platform \( p \) during day \( t \).

We normalize these time series to remove dependencies on the frequencies of posting as follows: For general YouTube shares, we calculate the proportion of posts that contain links to YouTube \( \rho_{yt,t} = v_{p,t}/n_{p,t} \), and for AIN/conspiracy/makeup videos, we calculate the proportion of daily YouTube links that contain either of these types: \( \rho_{X,t} = X_{p,t}/v_{p,t} \forall X \in \{ a, c, m \} \). Table 4 shows the means of these values and their changes before and after YouTube’s announcement, demonstrating that these changes are generally quite small, often fractions of a percent. While the factors influencing these changes are varied, from YouTube’s internal changes to content creator response to seasonality, we see consistent decreases in general YouTube and AIN sharing and increases in conspiracy and makeup sharing in both platforms.

Table 4. Changes in YouTube sharing before and after YouTube’s announcement, operationalized as the proportion of posts containing links to YouTube and the proportion of YouTube shares linking to AIN, conspiracy, and makeup videos. Mean changes in these proportions show both general YouTube and AIN sharing are decreasing, whereas sharing of conspiracy videos and makeup videos are increasing.

| Sharing Type           | Twitter |                  | Reddit |                  | Pre- | Post- | \( \Delta \) | Pre- | Post- | \( \Delta \) |
|------------------------|---------|------------------|--------|------------------|------|-------|-------------|------|-------|-------------|
| General YouTube Sharing| \( \rho_{yt,t} \) | 0.8806%          | 0.5792%| –34.23%          | 8.9685%| 7.9592%| –11.25%    |      |       |             |
| AIN Sharing            | \( \rho_{a} \)    | 0.1336%          | 0.1265%| –5.314%          | 0.3407%| 0.2761%| –18.96%    |      |       |             |
| Conspiracy Sharing     | \( \rho_{c} \)    | 0.0901%          | 0.1789%| 98.56%           | 0.2751%| 0.3330%| 21.05%     |      |       |             |
| Makeup Sharing         | \( \rho_{m} \)    | 0.0025%          | 0.0091%| 264.0%           | 0.0558%| 0.0592%| 6.093%     |      |       |             |

4.1 Time Series Data

Figure 1 presents the changes in general sharing of tweets, Reddit submissions, and links to YouTube videos over these 8 months. From this figure, one can see the number of tweets on Twitter varies from three to four million per day with a slight upward trend. For Reddit, submissions per day varies between 200 thousand and 500 thousand with a strong weekly periodicity and also exhibits an upward trend. Examining the proportions of posts containing links to YouTube presents a different trend, however, with both Twitter and Reddit seeing a decrease in posts with links to YouTube over this 8-month timeframe. Despite this similar trend, one should note YouTube videos are much more popular on Reddit than they are Twitter, accounting for approximately an order of magnitude more submissions than tweets.

A distinct point from Figure 1 is the marked drop in proportion of tweets containing links to YouTube \( \rho_{yt} \) on 1 February 2019. This significant drop can be attributed to a change to YouTube’s content publishing platform that went into effect on this day. According to a support notice posted by YouTube’s engineering team, YouTube has removed the “Automatic sharing of YouTube activity to Twitter” feature from content creators’ “Connected apps” options, removing a pathway through which content creators could automatically share to Twitter when they uploaded a new video.

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\( \text{https://support.google.com/youtube/thread/989408?hl=en} \)
This drop in proportions of tweets linking to YouTube videos is attributable to YouTube's disabling the "Automatic sharing of YouTube activity to Twitter" capability in its creator suite.

Fig. 1. Time series data on daily posting of tweets and submissions and proportions of posts that contain YouTube links. The red line marks January 25, the date of YouTube’s announcement. One should note the significant decline in the proportion of tweets containing links to YouTube videos that occurs on 1 February, which is attributable to a change in YouTube’s content creator suite that removed the “Automatic sharing of YouTube activity to Twitter” capability.

Fig. 2. Time series data on daily proportions of videos shared that contain links to AIN, conspiracy, and makeup videos. The red line marks January 25, the date of YouTube's announcement. AIN sharing appears to taper off to a small amount in late May.

Relatedly, Figure 2 shows the variations in proportions of sharing for the three video types we examine. This figure demonstrates that AIN sharing appears marginally stable with a decreasing
tail in the middle of May 2019. Conspiracy sharing appears to experience an uptick in the post-treatment regime. Makeup videos appear more prevalent on Reddit than Twitter with more bursts in Reddit in the pre-treatment regime.

These findings have two implications: First, the first demonstrates that YouTube’s actions do have a significant impact in sharing across platform boundaries. Second, YouTube’s change to its automatic sharing confounds our ability to identify the impact of YouTube’s recommendation system changes and therefore necessitates a more sophisticated approach, which we introduce below.

5 MODELING YOUTUBE’S IMPACT IN PRE- AND POST-TREATMENT SHARING

Given the difficulty in separating factors that contribute to changes in the aggregate sharing patterns shown in Table 4, we introduce an alternate ITS log-log linear regression model to predict volumes of general YouTube videos, AIN-authored videos, and conspiracy videos. In principal, this ITS model is similar to that employed by Chandrasekharan et al. [3], and more detail can be found in the ITS tutorial by Bernal et al. [1]. An ITS model is particularly applicable in this context as it allows us to capture both level and trend changes brought about by an intervention (here, YouTube’s change). Because platform effects and time lags likely impact the cross-platform sharing (e.g., a de-recommended YouTube video may be on the front page of Reddit the day before YouTube institutes its change, leading Reddit users to see this video for some period of time after YouTube’s change), we expect the effects of YouTube’s intervention to intensify over time, and the ITS model allows us to capture this effect with its trend parameter.

We first model the sharing of AIN-authored videos in Equation 1, where $v_{p,t}$ captures the number of videos posted on day $t$ to platform $p$, $a_{p,t-1}$ captures the lagged auto-regressive properties of sharing (i.e., the influence of the prior day in sharing), $T_t$ is an indicator function for whether the day $t$ is after 24 January 2019, $d_t$ denotes the number of days after 25 January 2019 (and is equal to zero prior to that date), and $\beta_i$ variables are the coefficients we learn for each factor. We likewise model conspiracy and makeup videos in Equations 2 and 3 respectively. One should note that in these models, sharing volumes are log-transformed to account for the highly skewed nature of scale-free social networks. Furthermore, we focus only on the percentage on videos shared on each platform rather than the percentage of posts because overall post volumes are subject to numerous additional factors. Of particular concern is YouTube’s change to its content creator suite, as shown in Figure 1, that has artificially reduced the overall number of YouTube videos. Instead, our focus is on the distribution of videos since YouTube is not decreasing the number of videos it recommends.

\[
\ln(a_{p,t} + 1) = \beta_1 \ln(v_{p,t} + 1) + \beta_2 \ln(a_{p,t-1} + 1) + \beta_3 T_t + \beta_4 d_t 
\]  
(1)

\[
\ln(c_{p,t} + 1) = \beta_1 \ln(v_{p,t} + 1) + \beta_2 \ln(c_{p,t-1} + 1) + \beta_3 T_t + \beta_4 d_t 
\]  
(2)

\[
\ln(m_{p,t} + 1) = \beta_1 \ln(v_{p,t} + 1) + \beta_2 \ln(m_{p,t-1} + 1) + \beta_3 T_t + \beta_4 d_t 
\]  
(3)

The coefficient $\beta_3$ allows our model to capture a level change in the overall amount of sharing, whereas $\beta_4$ captures changes in trend. This trend mechanic is especially appropriate in this context because we do not actually know when YouTube’s modification was rolled out on the platform; as YouTube’s announcement mentions, their modified recommendation algorithm “will be a gradual change” [22]. Therefore, as time moves away from the announcement, one would expect the impact of this change to increase over time. In the following subsections, we break down results from these models.
5.1 Pre- and Post-Treatment Sharing – AIN Videos

As mentioned in Equation 1, our ITS model has four primary factors explaining the daily sharing of AIN videos \( a_{p,t} \) on \( p \in \{ \text{Reddit, Twitter} \} \) on day \( t \): volume of posts containing videos \( v_{p,t} \) on that platform and day, the lagged number of AIN videos shared on that platform on the prior day \( v_{p,t-1} \), whether the day is before or after the announcement date \( T_t \), and the number of days since the announcement was made \( d_t \). The expectation for AIN and conspiracy videos here is that \( \beta_3, \beta_4 < 0 \) in both Twitter and Reddit, especially as we have evidence that YouTube’s change to its recommendation system reduces the number of AIN videos recommended.

Table 5 presents results for AIN video sharing in Twitter and Reddit. As shown, the distance from YouTube’s announcement \( d_t \) does manifest with a significant and negative effect on trends in AIN sharing for both Twitter and Reddit. This model suggests that, for each day that passes since the announcement, we can expect approximately \( 0.3{\%} \) fewer AIN videos shared on both platforms. The level factor \( \beta_3 \) (being before or after the treatment date) is not significant in either platform, consistent with a phased roll-out of YouTube’s change. As expected, the number of posts linking to YouTube on a given day \( v_{p,t} \) and lagged sharing are both significant, positive factors in predicting daily sharing of AIN videos.

Table 5. Capturing impact of YouTube’s announcement on the sharing of AIN-produced videos in Twitter and Reddit with a log-log linear regression ITS model. Model results show a consistent reduction in AIN sharing significantly correlated to the distance from YouTube’s announcement (i.e., the treatment) in both Twitter and Reddit.

| Predictor                  | Twitter | Reddit |
|----------------------------|---------|--------|
|                            | \( \beta \) | Std. Err. | \( \beta \) | Std. Err. |
| YouTube Volume \( v_{p,t} \) | 0.1330*** | 0.018    | 0.1073*** | 0.019 |
| Lagged AIN sharing \( a_{p,t-1} \) | 0.6209*** | 0.051    | 0.7554*** | 0.042 |
| Treatment \( T_t \) | 0.0784 | 0.076    | 0.1237 | 0.063 |
| Distance from Treatment \( d_t \) | −0.0036*** | 0.001    | −0.0033*** | 0.001 |
| Observations | 242 | 242 |
| \( R^2 \) | 0.988 | 0.995 |

Note: *\( p < 0.05; ** p < 0.01; *** p < 0.001 \)

5.2 Pre- and Post-Treatment Sharing – Conspiracy Videos

The model of YouTube’s announcement on the sharing of conspiracy videos follows a different pattern than the AIN model. Table 6 suggests that, unlike above, YouTube’s announcement has had no significant impact on trends in sharing of conspiracy videos, but the overall level of conspiracy sharing increases significantly on Twitter during the post-treatment regime. The Twitter model suggests that, since the announcement, conspiracy video sharing has increased by approximately 27% on the platform.

5.3 Pre- and Post-Treatment Sharing – Makeup Videos

Recalling that the above models are meant to instrument the effect YouTube’s announcement about its recommendation system has had on the sharing of specific types of anti-social content, this section turns to a type of video that should not be impacted by this announcement or engineering change. As shown in Table 7, we find no significant change in the level or trend in sharing of makeup videos on either Twitter or Reddit between the pre- and post-treatment regimes. One
Table 6. Capturing impact of YouTube’s announcement on conspiracy video sharing in Twitter and Reddit with a log-log linear regression ITS model. Models show an inconsistency between Twitter and Reddit wherein conspiracy sharing on Twitter sees an increase following the treatment of YouTube’s announcement, but this effect is not significant in Reddit.

| Predictor                  | Twitter               | Reddit               |
|----------------------------|-----------------------|----------------------|
|                            | $\beta$ | Std. Err. | $\beta$ | Std. Err. |
| YouTube Volume             | $v_{p,t}$ 0.1826***   | 0.018                | 0.2723*** 0.025 |
| Lagged conspiracy sharing   | $c_{p,t-t}$ 0.3892*** | 0.059                | 0.3390*** 0.059 |
| Treatment                  | $T_t$ 0.2681*         | 0.115                | 0.1300 0.079 |
| Distance from Treatment    | $d_t$ -0.0001         | 0.001                | 0.0007 0.001 |
| Observations               | 242                  | 242                  |
| $R^2$                      | 0.971                | 0.992                |

Note: $^*$p < 0.05; $^{**}$ p < 0.01; $^{***}$ p < 0.001

should note though that the proportion of variation explained by the Twitter-specific makeup model is lower than the other models ($R^2 = 0.513$ whereas all other models obtain $R^2 > 0.9$), though this issue may result from the fact that we have fewer makeup videos than other video types.

Table 7. Capturing impact of YouTube’s announcement on makeup video sharing in Twitter and Reddit with a log-log linear regression ITS model. The models show, as expected, no significant effect of YouTube’s announcement on the sharing of makeup-related videos in either platform.

| Predictor                  | Twitter               | Reddit               |
|----------------------------|-----------------------|----------------------|
|                            | $\beta$ | Std. Err. | $\beta$ | Std. Err. |
| YouTube Volume             | $v_{p,t}$ 0.0191***   | 0.006                | 0.1218*** 0.015 |
| Lagged makeup sharing      | $m_{p,t-t}$ 0.4955*** | 0.057                | 0.4912*** 0.057 |
| Treatment                  | $T_t$ -0.0700         | 0.116                | 0.1306 0.140 |
| Distance from Treatment    | $d_t$ 0.0025          | 0.001                | -0.0021 0.002 |
| Observations               | 242                  | 242                  |
| $R^2$                      | 0.513                | 0.928                |

Note: $^*$p < 0.05; $^{**}$ p < 0.01; $^{***}$ p < 0.001

5.4 Threats to Validity

A potential threat to validity in this work stems from our method for selecting thematically related videos from Reddit. Specifically, the karma threshold used to identify community-selected conspiracy and makeup videos may inadvertently impact the above models. To investigate this potentiality, we have also run the conspiracy- and makeup-video models using all videos posted to the conspiracy and makeup subreddit communities, resulting in 7,212 conspiracy videos and 925 makeup videos respectively. With these additional videos, the direction and significance of all but one model remains unchanged. The results from both Reddit models are preserved (i.e., no significant effect), as are the results from the Twitter conspiracy model (i.e., we see an increase in the level of conspiracy sharing). For the model of makeup sharing in Twitter, however, our robustness check reveals a significant ($p < 0.05$) increase in the trend, which may be attributable to the increase in popularity of the makeup communities, as discussed in the Reddit blog post mentioned above.
Additionally, the use of link sharing as a metric for evaluating the impact of YouTube’s announcement omits information consumption patterns (i.e., who is seeing these videos) and audience size. While the best solution to this threat would be to use impression and view data, this information is highly protected by the platforms and difficult to collect. As such, we use link sharing as a proxy for consumption and note that we make an important distinction between the proportion of shared links and the proportion of shared videos. Recommendation changes should affect this composition of shared videos under the expectation that changes to the composition of recommendations, as YouTube claims, will be reflected in changes to composition of what is shared, regardless of audience size.

A more problematic threat to validity is that of our excluding Facebook’s role in the sharing of these videos. Facebook’s massive user base and population of topic-specific pages and groups could be a gathering place for people interested in the potentially anti-social topics YouTube wishes to target. Given many internet users engage across several platforms [15], variations in sharing of AIN videos could result from an action taken by Facebook similar to that of Reddit described in Chandrasekharan et al. [3]. This issue is difficult to address given current data limitations from Facebook, but we are actively working on future research to address this threat.

6 DISCUSSION

Apparent from these studies are two findings that persist across platforms: the popularity of YouTube sharing is falling (see Table 4), and YouTube’s announcement and resulting change to their recommendation algorithm seems to have had a significant suppressive effect on the sharing of AIN-produced content (see Table 5). While we cannot definitively know from this data and without confirmation from YouTube whether these phenomena are related to YouTube’s internal changes, the consistency across platforms is telling.

Regarding the consistent, significant drop in proportion of YouTube links to AIN-produced videos, it is comforting to see this result persist across Twitter and Reddit, as this consistency enhances this result’s validity. With Suzor showing AIN videos have received fewer recommendations following YouTube’s announcement [18], that past work coupled with our results support the notion that YouTube’s actions have played a role in this decrease in cross-platform sharing. At the same time, it is difficult to make this causal claim definitively, as the time series in Figure 2 shows AIN sharing only seems to taper off in the middle of May rather than earlier in our treatment regime. An alternative explanation here is provided by YouTube itself, as they announced in early June that supremacist content or “videos that promote or glorify Nazi ideology” will be removed from the platform [23]. Though this more recent announcement states these new content policies went into effect on June 5, they mention “it will take time for [YouTube’s] systems to fully ramp up and [YouTube will] be gradually expanding coverage over the next several months” [23]. It is therefore possible that either YouTube’s recommendation engine changes have a significant lag, or AIN-related content has been removed as a precursor to the June 5 announcement. To address this potentiality, we have checked our initial set of 40,764 AIN-produced videos to see how many remain on YouTube’s platform, and we find 37,612 of these 40,764 remain; that is, only 7.732% of videos in our AIN set have been removed as of July 2019. We also do not know when these videos were deleted. This uncertainty coupled with YouTube’s claim of a hard 5 June enforcement period and that 14.23% of our conspiracy videos have also been deleted from YouTube without seeing a similar effect makes it seem unlikely these deleted videos would be sufficient to account for the consistent effects seen here. Interestingly however, YouTube’s more recent change to deleting supremacist content opens a path for future work in which the effects of de-recommendation can be compared to the effects of content removal in sharing.
This point of removing content from YouTube’s platform is important in that it may be the most impactful way to reduce exposure to this harmful and misinforming content. As shown in Chandrasekharan et al., wholesale banning and deletion of anti-social users and communities has proven effective within a specific platform [3], but YouTube is in a more powerful and unique position to affect the broader ecosystem given its role as a massive content host to which many other platforms link (as distinct from Reddit, as Reddit is primarily a content aggregator). If YouTube were to delete such content, as they have announced with supremacist videos, there is little use in linking to deleted videos, regardless of platform. Going even further, this deletion would address potential issues within Google’s ecosystem in which the search engine can expose individuals to this misinforming and harmful content either by directly linking to YouTube videos or by capturing posts on Reddit or Twitter that link to these videos; if these videos have been deleted from YouTube, these alternate vectors would be addressed. Instead, finding links to videos that have merely been removed from recommendation will likely not dissuade the interested.

While deletion may be the most effective strategy to mitigate YouTube’s role in spreading misinforming and harmful content online, making YouTube responsible for policing what is considered “harmful” discourse introduces its own difficulties. Since YouTube does not provide a mechanism through which the public can identify this harmful content, an individual is given little feedback if she inadvertently stumbles upon such a video (e.g., from a link on Facebook, WhatsApp, or Twitter). Likewise, a content creator whose videos are flagged by this system has no way of knowing and therefore no recourse in challenging YouTube’s classification. Given YouTube’s position as the dominant video sharing platform and its lack of transparency and the absence of regulatory incentives to support the public good, making YouTube this sole arbiter of what is considered allowable concentrates significant political and informational power into a single entity.

6.1 Growing Conspiracy Content

An additional difficulty particularly germane to this discussion is the ambiguity in defining “misinforming and harmful” content. In our study, YouTube’s action appears to result in a significant increase in the level of conspiracy-related videos in Twitter. While it could be that the propagation of conspiracy-related videos is entirely separate from YouTube’s recommendations, we instead propose two other explanations:

One plausible explanation may lie in errors in our sampling strategy and whether YouTube videos popular on Reddit’s conspiracy communities are sufficient for identifying conspiracy videos. Since we have little insight into which videos YouTube actually identify to be conspiracy content, it is difficult to say with confidence that we are capturing the same content YouTube is excluding from recommendation. In fact, YouTube’s announcement makes no specific mention of conspiracy videos, with mainstream media primarily introducing this label. This “conspiracy” label is additionally problematic since legitimate videos that explore conspiracies may be caught up in this collection. E.g., one could see the entire series of “Ancient Aliens” produced by the History Channel, of A&E Television Networks, LLC be identified as conspiracy content. While it is unlikely this content is harmful or misinforming, the line separating this content is far from clear.

To address this explanation, human annotators could manually check the videos sampled from Reddit’s conspiracy communities and remove non-conspiracy content, which would at least address concerns about how much conspiracy content we are actually measuring (though other factors like whether YouTube agrees with our human labels would remain problematic). Alternatively, we could focus on specific conspiracies around vaccinations, medical cures, Holocaust denial, and the September 11, 2001 terrorist attacks, as YouTube explicitly calls these videos out in their announcements. This topical focus may be brittle as new conspiracies emerge, and, since we have no way of knowing whether a particular anti-vaccination video is removed from recommendation,
we are left with the same uncertainty in overlap. Perhaps the most correct path forward would be to partner with YouTube and obtain a listing of videos YouTube has identified as conspiracy, but this approach would require platform-level buy-in.

Another more troubling explanation for the growth in conspiracy content stems from what replaces the content YouTube is no longer recommending. Holding other quantities equal, removing harmful videos from recommendation opens slots for new videos to be recommended. It is therefore possible that the audience to which these harmful videos would be recommended are instead recommended the more innocuous conspiracy videos we have identified, as these conspiracy videos may be semantically or socially adjacent to the harmful or misinforming content. That is, this audience may have then inadvertently been diverted for harmful content to this conspiracy content. Without additional insight from YouTube about how this mechanism works and whether harmful videos are replaced with the next most similar video or with a more pro-social video, we are limited in understanding this interplay. It is nonetheless important to consider these unintended consequences and whether YouTube’s actions create new incentives for more subtle misinformation and harmful content.

7 CONCLUSIONS

Ultimately, this work suggests, at least with AIN content, YouTube’s efforts appear to have had a pro-social effect on cross-platform sharing. While it is unlikely this approach will affect niche, anonymous communities and individuals who are already predisposed to conspiratorial thinking or “corrupted epistemology”, as coined by Sunstein [16], reducing wide exposure to such content is likely a social good. As concerns about YouTube and its role in misinforming and radicalizing individuals (as described by Ribeiro et al. [14] and Tufekci [19]) increases, it is good to see the platform take steps to address these issues that appear to have an effect rather than being simply lip service.

From a more general perspective, the evidence outlined herein suggests removing potentially harmful content from recommendation strikes an effective pro-social balance between allowing anti-social or subversive views to remain available without actively promoting and propagating this content. That is, individuals have the right to share their views but do not have the right to the platform’s assistance in monetizing those views. Other platforms could employ similar strategies to reduce the spread of such content, as explored by Reddit with quarantining subreddits and WhatsApp in preventing individuals from sharing links more than five times. Twitter could employ a similar strategy by removing anti-social content from trending and discovery sections, and Facebook could do the same in preventing specific content from getting recommended. More draconian approaches could disable native retweeting of specific content or disable native sharing for anti-social content; critically, individuals could still share this content manually, but adding an extra step to the propagation of such content could have a wide impact.

That said, we should be concerned about the wholesale application of this approach without further research into potential unintended consequences and what kinds of content get propagated instead. The growth we see in conspiracy content on Twitter may be one such unintended consequence, with borderline conspiracy content that was not classified as harmful receiving more recommendations in place of the harmful content that was removed. Without additional transparency, we have little insight into what this borderline content is that survives YouTube’s classification pipeline but is still potentially misinforming; i.e., where is the line between harmful and unharmful content and does content close to this line end up spreading even more? Applying such automated classification pipelines without careful and transparent consideration repeats the kinds of choices that brought online platforms to this point in the first place. Additional information
and error analysis on the performance of YouTube’s automated classification pipeline and
details on the qualitative human assessments are necessary for this insight.

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