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Politicization and Right-Wing Normalization on YouTube: A Topic-Based Analysis of the "Alternative Influence Network"

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Scholarship has highlighted the rise of political influencer networks on YouTube, raising concerns about the platform's propensity to spread and even incentivize politically extreme content. While many studies have focused on YouTube's algorithmic infrastructure, limited research exists on the actual content in these networks. Building on Lewis's (2018) classification of an "alternative influencer" network, we apply structural topic modeling across all text-based autocaptions from her study's sample to identify common topics featured on these channels. This allows us to gauge which topics appear together and to trace politicization over time. Through network analysis, we determine channel similarities and evaluate whether deplatformed channels influenced topic shifts. We find that political topics increasingly dominate the focus of all analyzed channels. The convergence of culture and politics occurs mostly about identity-driven issues. Furthermore, more extreme channels do not form distinct clusters but blend into the larger content-based network. Our findings illustrate how political topics may function as connective ties across an initially more diverse network of YouTube influencer channels.

Keywords: YouTube, influencers, right-wing politics, politicization, normalization, computational social science

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YouTube has been described as a breeding ground for ideological networks on the right (Ingram, 2018; Kaiser & Rauchfleisch, 2018). The platform's architecture combines broadcasting features with recommendations that foster the formation of communities and networks around shared ideas and ideologies (Munger & Phillips, 2022). The coexistence and potential interaction of various channels and their respective user bases is arguably one of the site's most important functions. Previous research has focused on YouTube's recommendation algorithm: While the content on the platform includes more mainstream and politically extreme viewpoints, the recommendation feature connects channels in a way that can draw users into a "rabbit hole" of increasingly extreme ideological content (Kaiser & Rauchfleisch, 2019; O'Callaghan, Greene, Conway, Carthy, & Cunningham, 2015).

Another strand of research has sought to understand the emerging structures between political influencer channels. Rebecca Lewis's (2018) study of the "reactionary right on YouTube" described a network of content creators, established through collaborations and guest appearances across ideological lines, as a "coherent discursive system" termed the "Alternative Influence Network" (p. 8). This qualitative study looks at connections between YouTubers to provide a detailed description of the tonality and overall focus of channels that deliberately carve out niche positions to attain countercultural appeal. This provides a snapshot of an emerging right-wing information ecosystem—constituted by a diverse set of interconnected actors who engage in political content production and distribution online (Wiard, 2019). While the study by Lewis (2018) did not aim for a large-scale analysis of the information disseminated by these YouTube channels, scholars have since started to apply quantitative methods to better understand these communities and the proliferation of political content on the platform (Munger & Phillips, 2022; Rauchfleisch & Kaiser, 2020).

Our work contributes to these strands of research with a large-scale, multimethod study to better understand the actual content that is distributed via the channels of the "Alternative Influence Network" and its development over time. We believe it is important to understand YouTube influencer channels as dynamic actor types, connected not only via direct forms of engagement or through overlap in their user bases but also by the topical foci they converge on. To do so, we combine automated structural topic modeling, manual classification of topic categories, cluster analysis, and topic-based network analysis. Our study's seed list comprises Lewis's (2018) initial set of 81-networked actors and ultimately provides 61 analyzable YouTube channels. Drawing on this set of channels, we process over 16,800 hours of video material from more than 51,526 videos, transcribed into text as provided via the closed caption feature, in a longitudinal study starting with a channel's respective creation date and ending in 2019.[2] Going beyond a specific snapshot of channels and communities, our analysis provides insights into what topics were circulated by these content providers and how they shifted over time.

[2] For a full list of the channels, as well as the codebook used to categorize topics, see our appendix, available here: https://www.dropbox.com/scl/fi/n0aacm6nczaml6oe0fybt/Kn-pfer-et-al-YouTube-Topics_Appendix.docx?rlkey=lhyyl6i2kby4wreauxh417kj3&dl=0.

We proceed in four steps. First, we provide an overview of the literature on YouTube channels as a hub for right-wing[3] content. Here, we also introduce our main concepts of *normalization* and *politicization*, which inform our main research questions. We then introduce our study design, data, and methodological approach. The third section presents our findings, which substantiate many of the concerns raised by previous studies that focus on these novel actor types (Lewis, 2018; Maly, 2020; Munger & Phillips, 2022) and further illustrate how these come to form connections via a shared focus on increasingly political content. The fourth and final sections discuss these findings in the context of their broader implications for platforms and content moderation and end with remarks on our study's limitations and potential avenues for future research.

Literature Review and Research Questions

Concerns about YouTube's potential for spreading fringe viewpoints and extreme ideologies have spurred a wide range of research relating to the distribution of various forms of ideologically extreme content on the political right. The heterogeneous set of actors and substantive positions within the right wing has led to a number of subclassifications, especially about less mainstream or centrist positions, such as new right, alt-right, extreme right, or radical right (Gidron & Ziblatt, 2019; Marwick & Lewis, 2017; Mudde, 2019, pp. 5–8). The different ideological positions associated with these monikers are often seen as highly dynamic and might shift in terms of who or what might be classified as such (Pirro, 2023). However, the more extreme positions and topics usually associated with the far end of the political spectrum tend to be more clearly associated with forms of authoritarianism, xenophobia, racism, anti-Semitism, fascism, and nativism (Eatwell, 1989; Rydgren, 2018).

One strand of studies focusing specifically on YouTube's propensity to host or even incentivize such communities and content has focused on the platform's recommendation algorithm. This research has shown that users who consume extreme right-wing content on the platform are likely to receive recommendations leading to similar extreme content (O'Callaghan, Greene, Conway, Carthy, & Cunningham, 2013; O'Callaghan et al., 2015). These algorithmically enabled connective pathways have frequently been described as narrowing the variety of content a user is exposed to on a specific platform. O'Callaghan and colleagues, for example, describe this process as an "immersion in an ideological bubble in just a few short clicks" (O'Callaghan et al., 2015, p. 459), while Kaiser and Rauchfleisch (2018) show that the recommendations connect extreme channels and thereby contribute to what they more explicitly refer to as "the formation of a far-right filter bubble" (para. 1).

Other studies have measured users' content consumption directly. Ribeiro, Ottoni, West, Almeida, and Meira (2020) differentiate between YouTube channels belonging to three communities, classified as "the Intellectual Dark Web," the "Alt-lite," and the "Alt-right"—forming a spectrum ranging from ideologically moderate to extreme (p. 131). The authors note a growth in supply (number of videos) and demand (likes, views) for all three communities. Based on a comparison of commenting users, their overlap, and their

[3] We use this term in its function as an umbrella concept, capturing "a coalition of heterogeneous political currents with distinct, and at times clashing, ideological visions and social bases of support" (Gidron & Ziblatt, 2019, p. 23), ranging from conservative or moderate-right, to more radical or far-right positions.

development over time, the study finds that the three communities converge in the sense that they increasingly share the same audiences. They also report a systematic "user migration" (Ribeiro et al., 2020, p. 132) that flows from the less extreme communities to the Alt-right. Meanwhile, a study by Hosseinmardi et al. (2021) based on individual users' browsing behavior and news consumption finds "little evidence for the popular claim that YouTube drives users to consume more radical political content" (p. 2), but does show that the watch time for far right and "anti-woke" news had grown substantially. Their study highlights the enduring relevance of YouTube "as part of a larger information ecosystem in which conspiracy theories, misinformation, and hyperpartisan content are widely available, easily discovered, and actively sought out" (Hosseinmardi et al., 2021, p. 2).

While the studies cited above tend to focus on various aspects of how YouTube's infrastructure might connect various communities to specific forms of content, another strand of research has sought to better understand the direct connective ties between influencer channels. With respect to the network structures among a set of actors collectively classified as the "reactionary right on YouTube," Lewis (2018) highlights the importance of personal and communicative connections between various content creators (p. 10). Based on a qualitative analysis of the video content from approximately 65 YouTube influencers across more than 80 channels, Lewis's (2018) study revealed that the channels are closely interconnected through guest appearances, citations, and cross-promotion. Lewis (2018) conceptualizes this set of media pundits, Internet celebrities, and social media influencers as a "coherent discursive system" (p. 8) termed the "Alternative Influence Network." Lewis (2018) argues that these channels adopt increasingly radicalized positions with countercultural appeal because of audience demand, the platform's incentive mechanisms, and personal or professional relationships between content creators. While this set of channels includes actors who have publicly self-identified as ideologically right wing or even far right, it also includes channels that are not ideologically focused from the outset, but engage in more casual topics, such as lifestyle advice or gaming reviews.

The coexistence of ideologically charged political and seemingly apolitical topics could be understood as a result of the networked information ecosystem provided by digital platforms (Davey & Ebner, 2017, p. 25). This relies on the affordances of digital media to produce, interconnect, distribute various content, and reflect an algorithmically enabled "metapolitical strategy" of right-wing ideologies (Maly, 2020, p. 3). This deliberate connection between culture and politics can function as a means of pursuing cultural hegemony through a positive, moderate intellectual positioning of far-right ideological values (Maly, 2019, p. 3). Such a strategy not only draws on the potential for connectivity embedded in digital practices but is also culturally integrated. As Maly (2020) argued, "Weddings and relation advice on YouTube can now become powerful pathways to far-right radicalization" (p. 19). Latching on to cultural issues is one way to popularize far-right ideology and contribute to the "normalization of ideas" (Maly, 2019, p. 1).

The concept of *normalization* more broadly describes a process through which ideologically extreme ideas might flow into broader public debates and discourses (Guardino & Snyder, 2013; Klinger, Bennett, Knüpfer, Martini, & Zhang, 2022; Wodak, 2015). In the context of far-right politics, this process is "geared toward the normalization of xenophobic, nationalistic and exclusionary discourses which were deemed unacceptable and morally repulsive merely a decade (or two) ago" (Cammaerts, 2018, p. 7). Normalization thus widens the "window of political possibility" (Miller-Idriss, 2020, p. 45) and expands the range of political ideas considered voiceable and acceptable at a given time. This process can play out in diverse contexts, including political and mediated discourses, as well as in the various spheres of online content distribution and youth-cultural settings. In fact, the multiplicity of spheres involved has been described as crucial to the strategy's success (Miller-Idriss, 2020, p. 68).

While previous studies such as Lewis's (2018) or Munger and Phillips (2022) have indeed shown that ideologically extreme channels connect directly to more moderate ones, wherein channels geared toward tech reviews or gaming news appear side by side with vocal proponents of far-right ideologies, we still know little about what this means in terms of the proximity of specific *topics* circulating among this network of content providers. To empirically analyze the distribution of content and the proximity of political to cultural topics, our first research question therefore reads:

RQ1: Which topics are most prevalent in the content of the alternative influence network and which (cultural or political) topics appear in proximity to one another?

As Munger and Phillips (2022) have shown in an enlarged version of the alternative influence network, the channels' ideological orientations also vary widely. The authors classify them into five categories, ranging from "Liberals" via "Skeptics" and "Conservatives" to "Alt-Lite" and "Alt-Right" (Munger & Phillips, 2022, pp. 15–17). In centering our analysis on topics rather than channel-level information and focusing on thematic clusters within the content these influencers collectively produce, our first research question allows us to address whether we do indeed observe dynamics of *normalization* as defined above on the level of topics rather than channels. In contrast, another potential observation would be more homogeneous thematic topic clusters that remain largely distinct from one another.

Beyond this, we might seek to uncover how the prevalence of specific topics develops over time. In this context, the concept of *politicization* can be understood as a process through which political topics are increasingly brought into deliberative spaces (cf. Zürn, 2014, p. 50): If politicization is in place, in other words, we would expect to find an increase in the salience of political or ideologically charged topics over time. Our second research question addresses these dynamics:

RQ2: How does the distribution of topics within the alternative influence network develop over time and do we find indicators of increasing politicization?

By focusing on a temporal dimension, we seek to facilitate a deeper understanding of the actual thematic content and the dynamics of how this network has potentially consolidated and changed. In this context, it is important to note that many channels of the alternative influence network do *not* characterize or present themselves as right wing—or even specifically as ideological or political. Instead, we deal with a diverse mix of channels and actor types that might have very different motives and incentives driving the content they generate and provide for their respective audiences, even if these overlap to some degree. While the initial study we draw our sample from labels all of these as being part of YouTube's "reactionary right," it also acknowledges that these initially consist of "a hodge-podge of Internet celebrities claiming a variety of political positions" (Lewis, 2018, p. 8), which may only come to focus on increasingly politicized content because of audience demand, platform infrastructure incentives, and communicative ties to one another.

Likewise, the notion of an alternative influence network we have used so far is driven by Lewis's (2018) observation that these channels are interconnected by cross-citations and a cross-promotion of ideas and might thus represent a somewhat organically emerging information environment. Yet, the question remains of how stable and integrated this network of channels actually is in terms of its output, that is, when it comes to forming ties based on the content distributed by the channels that form it. We latch onto this question by examining how important particular influencers are for the overall structure of this informational network. The question of network ties through which radicalized or inflammatory content is transported has been especially relevant in recent work exploring the effects of active interventions by platforms when it comes to penalizing specific channels (Buntain, Bonneau, Nagler, & Tucker, 2021; Rauchfleisch & Kaiser, 2021). For our study, we introduce channel-level meta-information as operationalization to define those channels as "extreme," which have since been deplatformed by YouTube.

The premise of a concept focused on individual excesses would be that these emerge within a particular community but might exert an outsized influence over the collective discourse associated with this group. Alternatively, we might conceive of a relatively integrated and stable informational network wherein the various actors collectively give shape to the content of circulating discourse. As of yet, it is unclear which of these two possibilities we are dealing with when it comes to the alternative influence network. By focusing on the content-based ties between individual channels, we address this research gap with our third research question:

RQ3: What channel clusters emerge within a content-based network and how do more extreme channels compare to the rest?

While the first two research questions center on the collective dynamics of normalization and politicization we find in the overall network, addressing this last research question will allow us to gauge whether these dynamics are confined to specific (extreme) channels. RQ1 thus provides us with insights into *normalization* dynamics by examining the topics and their relative proximity to one another. RQ2 highlights *politicization* processes and asks whether we see increasing convergence around particular political topics over time. RQ3 provides a more detailed analysis of the content-based network structures that emerge between influencers by introducing channel-level data to the topical content we find. In the following section, we explain how we set out to answer these questions by outlining the operationalization of our main concepts and explaining our methodological approach.

Data and Methods

Our study focuses on YouTube channels classified by Lewis (2018) as part of the alternative influence network. Lewis (2018) used a snowball approach to identify content creators and their collaborations. In total, she collected data on 65 influencers across 81 channels in the period from January 2017 to March 2018. We used Lewis's (2018) channel network to create a seed list, which formed the starting point of an automated collection of data for all videos published on these channels for the entire period, beginning with a channel's creation date until mid-2019 when we retrieved the data. Overall, we were able to collect data from 61 different channels, since not all of the original seed list provided the functions necessary for our analysis. We collected all available metadata and video information in July 2019 and removed stark outliers in terms of length from the data set (e.g., 24-hour podcast formats). The first video in our data set is dated as far back as August 14, 2006, the last one at July 16, 2019.

In addition to metadata, such as video time stamps, we relied on YouTube's autogenerated captions for textual content analysis. We used the open-source tool *youtube-dl* (Amine, 2019) to extract all available autogenerated captions for the videos in our sample. This approach is not without limitations, as nonaudio content information is not captured, and caption quality depends on various issues pertaining to video and sound quality. However, manual qualitative inspections suggested that for our computational text classification, as explained below, the data quality was sufficient. Overall, we extracted transcripts from 51,526 videos, which, based on the metadata, amounted to roughly 16,800 hours of material.

To categorize the content of videos in our sample, we applied structural topic modeling (STM) to all text-based captions using the *stm* package in R (Roberts, Stewart, & Tingley, 2019). Structural topic modeling enables the extraction of latent themes from the full corpus of video transcripts based on the bag-of-words approach, which estimates topics by identifying frequently co-occurring terms. In addition, STM allows for the inclusion of metadata—in our case, timestamps and channel information—as covariates in the model (Roberts, Stewart, & Airoldi, 2016). To choose the number of topics (K), we considered the topics' granularity, statistical fit, and interpretability of model solutions with varying numbers of K (Maier et al., 2018). Three researchers independently interpreted various model solutions, taking the words with the highest probability, the most frequent and exclusive words, and text examples into account. Based on these inspections, a model with 60 topics and video dates as a prevalence variable was chosen. This model provided the best fit and topic interpretability when compared with the results for lower and higher numbers. In particular, the 60 K solution resulted in better differentiation between topics when compared with a lower number of 40 K. Yet, in some cases (e.g., *Rebel Media*, *Ben Shapiro*), topics seem to still represent specific channels with a particularly high amount of content. Topics that were not evaluated consistently by the three researchers or appeared to provide no semantic meaning (e.g., a topic consisting of mostly stop words) were discarded.

Overall, this procedure resulted in 52 topics that could be reliably and soundly interpreted and thus formed the basis of our subsequent analyses. After an additional round of validating, interpreting, and discussing the results, we collectively applied labels to each of the topics. We should note that the process of attaching a singular label (often a single term or short combination of words) is intrinsically reductive and does not necessarily capture the full spectrum of what the longer list of words associated with each topic might provide. For example, the label "*Gaming*" might obfuscate the fact that the terms and contextual examples associated with this topic pointed, in part, toward discourses around "Gamergate." The topic label for "*Stefan Molyneux*" was applied to a topic that was clearly a result of an association with his particular channel within the text corpus—not so much a discussion about the person or his specific ideas. Likewise, the topic we labeled "*EU*" featured terms that also pointed toward EU skepticism and discussions around Brexit. In other words, the labels we applied are the results of qualitative evaluations of our team and should not be overinterpreted in and of themselves. For a general overview, these labels are nevertheless useful, and we provide additional context for their general classification and the broader context they might point to in the discussion of the results below.

In addition to automated text classification, we manually classified all 52 interpretable topics based on the top 20 most representative and most exclusive terms. This additional step of probing the topics for their most representative terms and looking at text-based examples provided an additional step of validation for the topic labels we had chosen, along with a deeper understanding of the context in which they appeared. This mixed-methods approach combines computational and manual classification and allows for improved systematization of the channels' content (Jacobs & Tschötschel, 2019). It also enables us to distinguish between three topical contexts, classifying topics into three separate categories: *political*, *cultural*, and *other*.

To do so, we developed a short codebook with instructions for three coders who independently assigned one of the three categories to each of the previously identified topics (see Appendix). We classified topics that refer to specific political events, institutions, and persons associated with the political sphere or to political discussions as *political* topics. This also includes normative debates on issues such as social identities and ideological values, which may have larger social implications for collective interaction. Topics that pertain to objects or events associated with lifestyle, entertainment, hobbies, or particular individual interests, without broader implications for the social sphere, were classified as *cultural* topics. Every topic not conforming to one of the two definitions was coded as *other*. Intercoder reliability reached a value of .92 (Cronbach's Alpha). Open discussions between the team of coders resolved the few remaining coding differences. It is important to underline that this categorization process took place on the basis of assessing the most representative terms for each topic—so while there might be debates over whether a given label should be placed in a specific category, the actual coding process was privy to more information. We present the results of these approaches in the following three sections.

Result 1: Topics, Clusters, and Normalization

To learn more about the actual content within the alternative influence network, we first looked at the aggregated results stemming from the automated topic modeling analysis. Table 1 provides an aggregated overview of the results of our classification process into the categories of *political*, *cultural*, and *other*, along with the aggregated proportions at which they occurred within the entire text corpus.[4] The first result we see here is that, in terms of both their overall number and proportionality, the category of *politics* clearly dominates.

Table 1. Topic Categories and Combined Expected Proportions.

Topic type	N Topics	Combined proportions
Politics	32	0.502
Culture	13	0.227
Other	15	0.117

[4] Note: the combined proportions do not add up to 100%, as the complete set also included topics that we were not able to accurately label.

In addition, Figure 1 provides an overview of the topics, their relevance within the whole network, and their co-occurrence within the same texts. We find a wide range of topics, some of which are more general in nature and others much more focused on specific individuals, places, or events. While we do see some variation in terms of specific topics' relative importance, as measured via proportionality values provided in parentheses, there is fairly little variation in terms of outliers here, with values ranging from 0.4 to 3.3. This indicates a fairly even representation of the topics our model identified within the entirety of the text derived from the analyzed channels. Moreover, no single set of topics stands out as being particularly dominant when compared with others. We are therefore confident that this list provides a broad and representative overview of the content produced by YouTube's alternative influence network over the timespan analyzed.

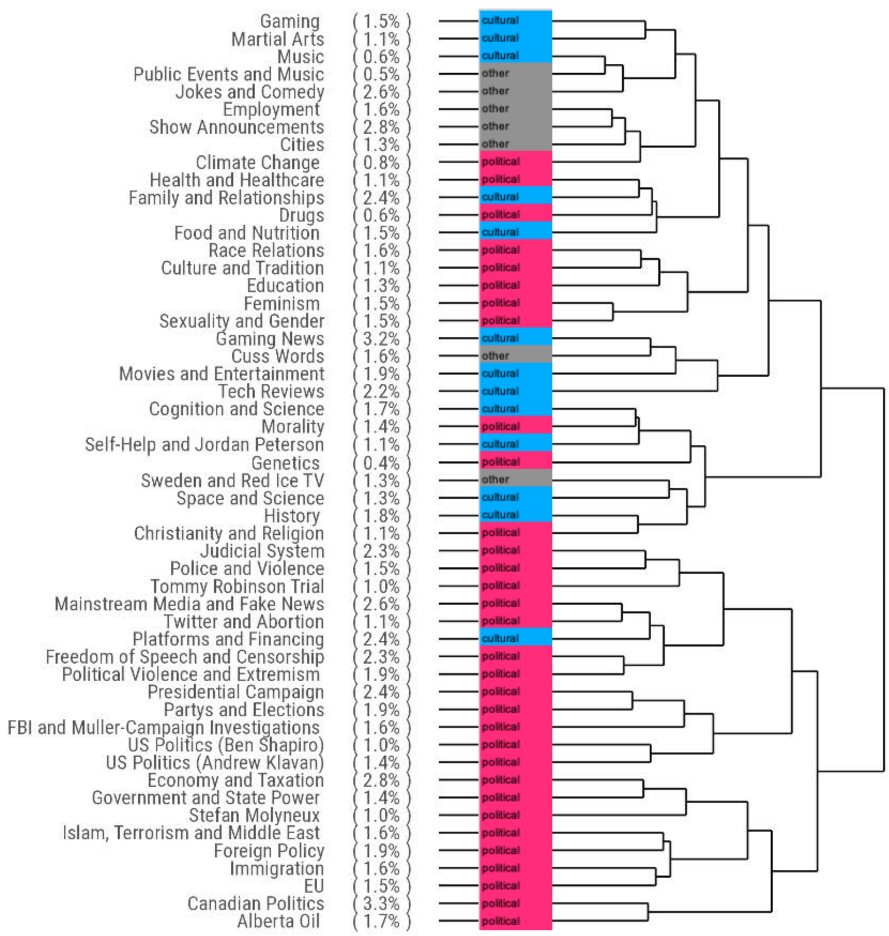

Figure 1. Dendrogram of labeled topics and their corresponding proportions in parenthesis.

Yet, there is more to this list than merely its initial descriptive value. Besides listing all identifiable and labeled topics along with their relative proportionality, the dendrogram shown in Figure 1 consists of clusters of topics that often co-occur within the same video captions. The clustering process structured through topics' proximity thus illustrates a topical spectrum, also indicated by the three categories highlighted in red, blue, and grey: the top of the list provides thematic clusters focused more on culture or entertainment (gaming, martial arts, music, etc.), as well as health and relationship advice, which appear in proximity to discussions on *Drugs* or topics around *Food and Nutrition*. Meanwhile, the bottom of the list consists of clusters more clearly geared toward specific political domains and policy fields, where *Islam, Terrorism*, and *Middle East* are connected to *Foreign Policy*, *Immigration*, and the *EU*.

In terms of our research question on potential forms of *normalization*, which we conceptualize as the occurrence of ideological topics in close proximity to more innocuous or even apolitical content, convergence within the middle parts of the topic list is therefore of particular interest. Here we find a mélange of such topics as *Climate Change* and *Health and Healthcare* interwoven with topical foci on *Family and Relationships* or *Food and Nutrition*. Another central cluster forms around *Gaming News*, *Movies and Entertainment*, and *Tech Reviews*, whose topics also appear to be relatively salient overall, as indicated by their comparatively high proportionality scores. This appears in proximity to a larger, clearly more political cluster focused on *Race Relations*, *Culture and Tradition*, and *Education*, which in turn is linked closely to *Feminism* and *Sexuality and Gender*.

This intermingling of topics associated with the realm of cultural production and consumption, on the one hand, and identity-driven politics, on the other, appears to be one central meeting point in which ideological topics converge with more innocuous ones within the analyzed network. From previous studies on the normalization of right-wing ideologies on the platform, it seems plausible to associate this particular convergence of clusters, at least to some degree, with formative discursive events like "Gamergate," which explicitly connected gaming culture to men's rights advocacy, misogyny, and antisocial justice activism (Marwick & Lewis, 2017, pp. 7–8). Similar dynamics appear to be at work within a cluster centered around *Self-help* and *Jordan Peterson*, which combines topics such as *Cognition & Science*, *Morality*, and *Genetics*. These appear in close proximity to the general topic of *History* and to the narrower and identity-driven topic of *Christianity and Religion*, and a combination of *Space and Science* to a topic shaped by the far-right Swedish YouTube channel *Red Ice TV* (n.d.).

Another convergent cluster combines the topic of *Platforms and Financing* (which mostly referred to means of monetization of content) with the broader topics of *Freedom of Speech and Censorship* as well as *Mainstream Media & Fake News*. We take this combination as indicative of an important formative theme within this particular set of content providers who collectively share the interest in providing alternatives to other, perhaps more mainstream media outlets—and who might be inclined to interpret forms of content moderation as a threat to their fundamental rights and livelihood. From these clusters, we may infer that topical proximity within the overall corpus of text analyzed here can reflect more than just the salience of a particular topic and may indicate something about the broader discursive contexts in which these would have occurred. Meanwhile, the bottom third of the dendrogram is populated exclusively with topics classified as political. What we observe here is a focus on particular political events or individuals, such as the U.S. *Presidential Campaigns* or the *Mueller* investigation. Yet, at the same time, we see these in close proximity to clusters with topics typically associated with right-wing U.S. politics, such as the discussions on *Abortion* in the context of *Political Violence and Extremism*, or the topic of *Taxation* in the context of *Government and State Power.* Similarly, *Foreign Policy* and the *EU* appear to be discussed in the context of *Immigration* and *Terrorism*.

Yet, the more important finding here pertains to the intermingling of content that we might otherwise not expect to be proximate in the sense that we observe a mix of *political* and *cultural* topics. In this regard, our findings reveal that, to the degree that *normalization* thus defined occurs, we observe it mostly about topics connected to markers of social or personal identity. Topics pertaining to gender and race play into larger thematic clusters on gaming and entertainment, while questions of morality and genetics intersect with content on science and psychology. Having established this, we now move on to the findings of our second research question.

Result 2: Politicization Dynamics Over Time

Next, we examine how the topics presented in this alternative information ecology developed over time. To do so, we introduced the respective video's dates as a prevalence covariate in our topic modeling. Figure 2 provides an overview of the results for each topic, grouped according to the previously assigned categories. For presentation purposes, we aggregated all *cultural* and *political* topics. Colors ranging from blue to red indicate the relationship between a given topic's expected proportion and time. Dark colors indicate a strong positive (red) or negative (blue) correlation, meaning that the topic's proportion would have increased or decreased over the period under analysis. P-values with corrections for multiple comparisons are indicated using plus and minus signs.

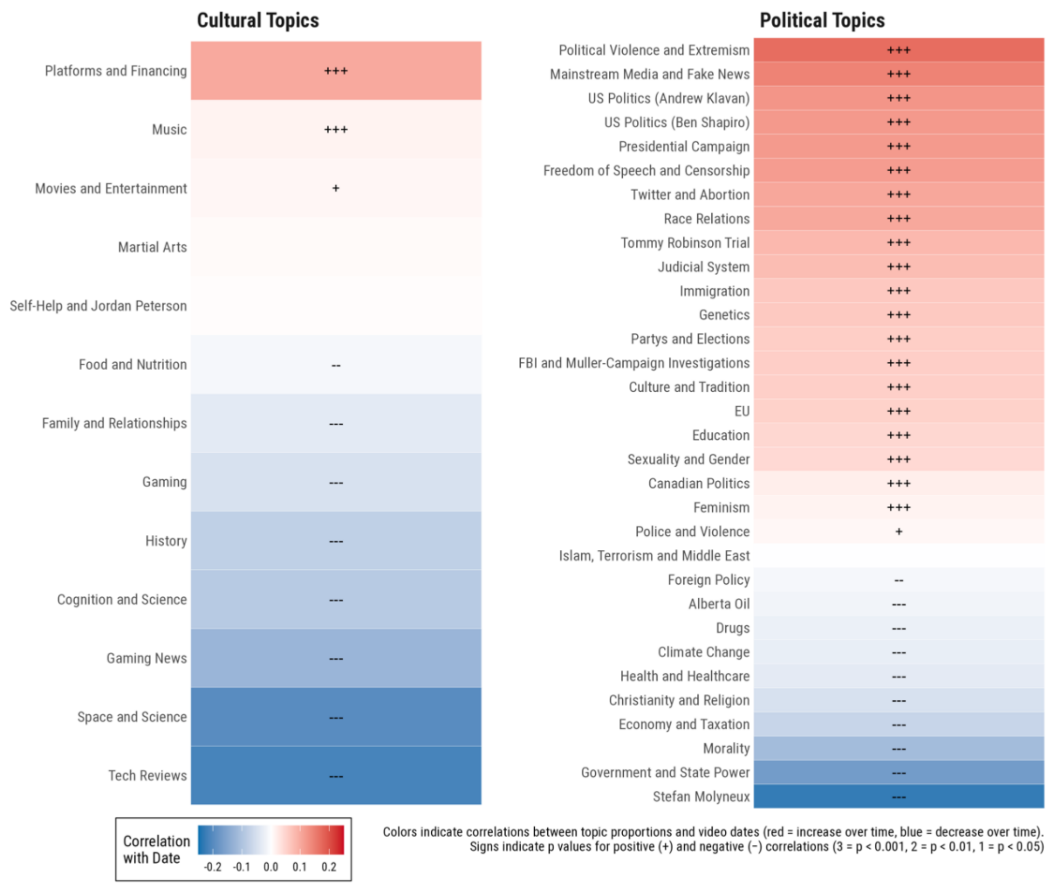

Figure 2. Topic proportions categorized and correlated with date.

In terms of the overall findings shown here, we see that most cultural topics show a decline in online attention. The only major exception is the topic of *Platforms and Financing*, which was shown to be closely associated with the political topics of *Free Speech & Censorship* and *Mainstream Media and Fake News*. It becomes clear that this general theme increased in importance within the network of alternative influencers. Meanwhile, we see an overall drop in entertainment- or consumerism-oriented content, marked by such topics as *Gaming* or *Tech Reviews*.

In contrast, political topics show a clear increase in salience. Of 32 topics classified as *political*, only 10 show a decline, while 21 show an increase. Importantly, some topics that belong to convergent clusters also follow the same trend as cultural topics. For example, topics that are related to *Health and Healthcare*, *Climate Change*, and *Christianity and Religion* also show a decline in salience, just as those cultural topics they were most closely associated with. What we observe instead is a dynamic by which clusters of specific political topics collectively gain in importance: This trend is most pronounced for the topic of *Political Violence and Extremism*, which was shown to be closely related to the also increasing topics *Mainstream Media and*

Fake News, *Freedom of Speech*, and *Abortion*. While the quantitative approach we have taken here can arguably show us little about how these topics are discussed, it is worth noting that all of these topics could be categorized as enjoying high levels of salience among contemporary right-wing actor types. Furthermore, we see an overall increase in political topics featuring prominent figureheads of the U.S. right (such as Ben Shapiro or Andrew Klavan).

In terms of our initial research question, these results clearly indicate a process of *politicization* within the content of the alternative influence network, as we observe an increase in the proportion of political issues. Furthermore, we observe a convergence of specific topical clusters that are indicative of talking points and personalities representative of right-wing ideologies. In other words, we not only observe a process of *politicization*, where political topics come to increasingly dominate over cultural ones, but we also observe a convergence of topics that can reasonably be associated with an increasing focus on right-wing agenda items.

Result 3: Centrality of Extreme Channels in a Topic-Based Network

To answer our third main research question, we gauged the relative importance of specific channels for the topical focus of the entire network. The goal was to establish whether the content produced by these channels was significantly impacted by a few selected channels that might be driving this overall focus and topic trajectory. To do so, we collected additional external data about the influencers in our sample and ultimately divided the group into two subsamples: channels that, at the time of analysis, had been officially banned from YouTube (n = 13) and those that were not (n = 48). Although we do not take the specific reasons for deplatforming into account, we still believe that this provides us with a group of channels that can reasonably be assumed to cater to more extreme ideological views than the aggregate of channels that had not been banned. We then ran the same analyses based on the aggregated proportionality of the topic categories for both groups.

Table 2 shows the topical focus in the comparison between banned and nonbanned channels. Although we could reasonably expect the proportion of political topics to be greater for the subsample of banned channels, we see that this is not the case. Instead, the category of cultural topics was slightly higher for this group than for nonbanned channels. Apart from this, the numbers do not seem to deviate strongly between the two groups. At an aggregated level, in other words, the overall trajectory of *politicization*, as observed above, does not seem to shift dramatically when we factor out deplatformed channels. Contrary to our expectations, this trend would even appear to grow stronger when considering only the sample of nonbanned channels.

Table 2. Expected Proportions of Topic Categories for Banned and Nonbanned Channels.

Topic type	**Nonbanned channels**	**Banned channels**	**All channels**
Politics	0.515	0.443	0.502
Culture	0.212	0.29	0.227
Other	0.116	0.122	0.117

To learn more about the relationships between channels, we analyzed the network that emerges when we compare them in terms of the content they feature. To visualize this, we created a network graph wherein edges between channels were weighted by topical similarities averaged across all videos for each channel. To identify edges, we applied the Meinshausen-Buhlmann method for high-dimensional undirected graph estimation (Zhao, Liu, Roeder, Lafferty, & Wasserman, 2012). Figure 3 presents a visualization of the results. The channels in our sample make up the network's nodes, whose sizes indicate the cumulated views for a given channel at the time of data collection, thus providing an indicator of their respective reach. The network's edges represent degrees of similarity between nodes, measured on the basis of the content these channels distribute. In other words, a given channel's position vis-à-vis other nodes is shaped by the similarity of topic-based content. Clusters of channels, therefore, also indicate channel groups that can be distinguished based on their shared topical repertoires.

We see that channels focused on lifestyle and philosophical advice, such as *Coach Red Pill* (n.d.), *Mouthy Buddha* (n.d.), or *Millennial Woes* (n.d.), appear in close proximity to *Jordan B Peterson* (n.d.). A transnational and ostensibly "identity politics" focused cluster made up of channels by *Lauren Southern* (n.d.), *Brittany Pettibone* (n.d.), *Kraut* (n.d.), and *Black Pigeon Speaks* (n.d.) forms around the outspokenly antifeminist *Sargon of Akkad* (n.d.). Meanwhile, a more U.S.-centric cluster emerges around avowedly right-wing partisan channels like *The Daily Wire* (n.d.), *PragerU*, *Mike Cernovich* (n.d.), *Steven Crowder* (n.d.), and *The Rubin Report* (n.d.). In the upper left corner, Joe Rogan's *PowerfulJRE* (n.d.) forms a particularly popular node. Rogan presents an interesting case, together with personalities such as *Tim Pool* (n.d.), who has consistently resisted being labeled as right wing or conservative (Munger & Phillips, 2022, p. 189). Indeed, Rogan (unlike Pool) is more directly connected to entertainment- or free-speech-focused content producers than to the more outspoken and self-described right-wing sets of channels.

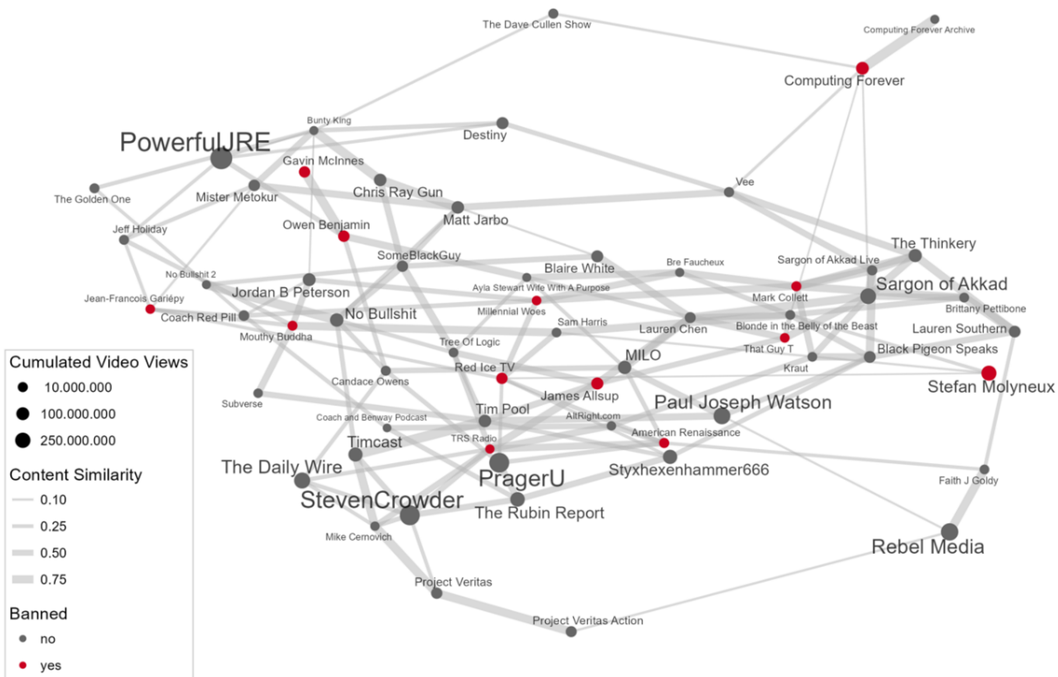

Figure 3. Network of channels based on content similarity.

Here, too, we identified the subsample channels that had been deplatformed at the time of writing and marked these in red. What stands out is that while these do appear to occupy central positions in the network, they do not form or latch onto a specific single cluster. While the majority form multiple connections to other channels, there are also more peripheral channels, such as the far-right political instigator *Gavin McInnes* (n.d.) or the conspiracy theory-focused *Computing Forever* (n.d.). To better quantify overall centrality differences, Table 3 includes multiple corresponding measures with minimum and maximum values and averaged values for the nonbanned and banned channels.

Table 3. Centrality Measures for Channel Network Based on Content Similarities.

Measure	**Minimum**	**Maximum**	**Average: Nonbanned channels**	**Average: Banned channels**
Degree	1	8	4.31	4.85
Betweenness Centrality	0	173.32	60.89	79.20
Eigenvector Centrality	0.05	1	0.43	0.50
PageRank	0.01	0.03	0.01	0.02

Overall, all centrality measures are higher on average for banned channels, indicating that these channels were somewhat more likely to bridge between channel groups with distinct topical repertoires.

However, the differences between the two types of channels are not substantial, suggesting that the content network does not represent distinct detached clusters connected only by banned channels as "gatekeeper" nodes. We take this to mean that more extreme channels do not fundamentally differ from other channels in the content-based network in the sense of forming their own distinct clusters. Instead, they blend into the overall network of alternative influencers and appear near other content-based clusters. Taken together with the results of our first two research questions, which highlighted the dynamics of *normalization* and *politicization*, we can conclude that these appear to be features of the entire network rather than specific and potentially more extreme channels.

Discussion

Overall, we found a wide variety of interpretable topics based on our large-scale, text-based analysis of the alternative influence network channels' content. The first finding of our study is, therefore, that the approach presented here, which applies STM to YouTube's autogenerated captions across 61 channels and more than 16,800 hours of material, provides a viable approach to studying large-scale trends in terms of content featured on the platform.

In terms of our main research questions, we find that the network of "alternative influencers" collectively shapes a discourse dominated by a blend of topics fusing cultural content with politics and ideology. While both categories seem to be intertwined, we also observe that political topics dominate overall. We observe a clear increase in the share of these topics over time. Looking at the network of channels overall, we therefore find an increasing convergence on topics such as *Political Violence and Extremism*, *Mainstream Media and Fake News*, *Freedom of Speech and Censorship*, and *Race Relations.* In this respect, we can interpret the development of topics featured in these channels as indicative of a process of gradual *politicization*, wherein agenda items often associated with far-right ideology (Mudde, 2019; Pirro, 2023) increasingly shape these channels' agendas.

Based on the comparison of the networks' content distribution between banned and nonbanned channels, it seems inaccurate to assume that specific forms of political and right-wing content would be limited to merely a subsample of channels. Rather, the share of political topics remained stable and even increased slightly within the remaining network of active nonbanned channels. This highlights the fact that the dynamics we observe in terms of *normalization* and *politicization* are not confined to specific informational silos or particularly extreme channels. Instead, we observe a network in which ideologically charged topics circulate widely and are discussed side by side with more mundane issues concerning entertainment or culture.

We take these findings to suggest that influencer channels and the networks they form should be viewed not only in their propensity to be connected via algorithmic recommendation systems. Rather, they must also be understood as collectively giving shape to an informational ecosystem, in forming a topic-bound network that, in turn, might give rise to other forms of connectivity. This has implications for how researchers might conceptualize pathways toward alternative information providers and how we understand YouTube as a platform for content and social interaction. As our research shows, this does not just apply to an implied audience but also to content creators who forge connections via convergence on particular sets of topics.

While our approach cannot explain what causes this increasing focus on ideologically charged political topics, it seems very plausible to assume that the networking activities highlighted by Lewis (2018) are likely to play a role here (pp. 35–42). These channels are brought together via a shared discourse that increasingly centers on—and caters to—a particular ideological *Weltanschauung* deliberately situated outside the bounds of more mainstream (i.e., less alternative) information providers. This convergence might imply that the connective ties which shape this informational ecosystem may grow stronger over time by focusing more specifically on a particular range of topics, which then become focal points across the entire network. The findings presented here, therefore, also reflect broader shifts in social media–based influencer activities, which seem to increasingly focus on political content and integrate corporate messaging to draw in potential funders or advertisers (Riedl, Schwemmer, Ziewiecki, & Ross, 2021). The concepts of *normalization* and *politicization* we employ might be seen as illustrative of larger trendlines in contemporary discursive spaces, where ideological actors seek to employ metapolitical strategies, while less ideologically driven content creators join them in their focus on particularly salient topics. Centering on topics rather than differences in actor types can therefore illustrate how closely connected specific sets of ideas might be to other thematic clusters.

Since Lewis's (2018) initial study, many of the channels in our sample have transitioned to other venues, while some have been deplatformed, as we point out above. A few, like Joe Rogan or Jordan Petersen, have become household names in contemporary American cultural and political discourse and have maintained sizable followings. The data we present here provide snapshots of the information environments that gave rise to such personalities. Moreover, our timespan covers formative shifts in the political landscape (online and off), which were accompanied by new discursive formations around the MeToo and Black Lives Matter Movements or the rise of right-wing populism in the United States and elsewhere. These topics also feature prominently in our data, making them valuable resources for understanding how these events were viewed and communicated. We therefore invite future scholars to use this repository for more detailed deep dives into these issues than the ones we were able to provide here.

Limitations and Conclusion

The results we have presented here and the conclusions we draw build on a previous classification of specific channels as constituting a network of "alternative influence" by the "reactionary right" (Lewis, 2018). While our own content-based approach underlines the fact that right-wing political topics increasingly dominate the output produced by these channels, we do not move beyond the seed list of channels provided via Rebecca Lewis's (2018) initial study. Much has since happened in terms of content moderation, active interventions by YouTube, and realignment among far-right actors on and off the platform. Future research might therefore seek to expand the scope of such analyses by developing new criteria for case selection and expanding our understanding beyond the scope of the channels under scrutiny here—perhaps by considering the more recent approach offered by Munger and Phillips (2022). In interpreting these results and generating future research questions, we need to acknowledge that we are dealing with an immensely dynamic sample of cases. Content found on YouTube generally, or even just within specific channels, is constantly in flux and provides a continuously moving target. Nevertheless, the observed processes of normalization and topical convergence by which specific types of political content spread over a population of different influencer accounts are illustrative of dynamics that need not be confined to this particular case.

We still need to be mindful of the fact that the results presented here are limited to text-based analysis of autogenerated captions. While this approach was able to generate meaningful results in our case, it is important to acknowledge how reductive this may be for gauging content based on what actual audiences would be likely to encounter. Text-based content analysis cannot capture simultaneously occurring multimedia effects and visual content. Yet, while more qualitative approaches might be able to study specific samples, large-scale analyses, such as the one presented here, will require significant innovative steps in making automated approaches to video-based material viable.

By analyzing topics and their respective proportionality, we merely know that these were featured and thereby brought to an assumed audience's attention. We do not know much more than that and cannot make claims about how these topics would have been discussed. It is entirely possible that some of these would have been mentioned or discussed in a critical or disapproving way, merely to highlight their existence. However, since the corpus is large and the salience of specific types of topics is great, we doubt that this would be the case for the vast majority of observations.

While our study rests on results generated by large-scale quantitative text analysis, any process of manually interpreting, labeling, and further categorizing topics involves a degree of subjectivity. While we are confident in our approach and the results we provide here, we acknowledge that other research teams might have chosen different topic labels or may have categorized these differently. However, since the trendlines we uncover are so stark, it seems doubtful that slight deviations in terms of categorization would yield fundamentally different results in the overall trajectory of what we report. Nevertheless, we invite open discussions and hope that others will seek to replicate our results.[5]

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[5] The data used for this study was retrieved via both the YouTube API and additional web scraping for the video captions. Unfortunately, this material cannot be shared publicly. Researchers interested in working with the data should please contact the authors of this study and highlight their intended use case.

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