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Exploring YouTube Political Communication Networks During the 2024 French Elections

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Abstract

In 2024, France was shaken by the far-right National Rally's victory in the European elections. In response to this unprecedented result, French President Emmanuel Macron dissolved the National Assembly, triggering legislative elections just two weeks later. A whirlwind campaign followed, partly on social media, as is now the norm, and concluded with the victory of a left-wing coalition. This article examines the YouTube activity of two key actors during this period—news media and politicians—and the commenting behavior they generated. We built a dataset of 35 news media channels, 28 politicians & party channels, 43.5k videos posted from three months before the European elections to one week after the second round of the legislative elections, and 7.4M associated comments. We examined upload activity and engagement across political orientations and used network analysis methods to uncover the structure of their commenting communities. We also identified politicians' appearances on news media channels and assessed their impact on commenting user bases. Our findings show that, among politicians and party channels, far-right and left-wing ones were significantly more active and received substantially higher engagement (views, likes, and comments) than other groups, with denser and more clustered commenting communities. About 7% of commenters commented across political orientations and were much more active than in-group commenters. News media channels tended to favor politically aligned guests, while centrist politicians were overrepresented. Finally, politicians presence in the videos of a specific news media channel increased the share of commenters who were active on this channel and political channels, regardless of their orientation.

1 Introduction

Over the past two decades, social media have become a central component of political communication, gradually supplementing traditional means such as radio, television and press interviews, and campaign rallies (Severin-Nielsen 2023). Social media allow direct communication between politicians and the public, bypassing journalistic mediation (Chadwick 2017), and enable two-way interaction as viewers can respond to and share politicians' content (Peeters et al. 2023). Populist movements, including far-right ones, have especially flourished online, fostering alleged ties with "the people" and amplifying cultural threat narratives through anecdotal sharing (Engesser et al. 2017). News media also increasingly use social media to promote content and engage audiences (Rajapaksha, Farahbakhsh, and Crespi 2024), alongside their own communication channels, such as TV, radio, and print. Despite leveraging social media to circumvent mainstream news outlets, frequently condemned by populist politicians as part of a corrupt elite (Engesser et al. 2017), many politicians, including those of the far-right, still re-purpose clips from news media appearances, clips that were also shared by news media outlets on their own social channels. This shows a complex relationship between politicians, news media, and social media.

One aspect of this relationship unrolls on YouTube where both politicians' videos and news media videos featuring politicians attract much interest and are highly commented by users, supporters or opponents (Wu and Resnick 2021). YouTube comments have been part of the platform since its early days and a majority of users have reported systematically reading the first two or three comments (Schultes, Dorner, and Lehner 2013). As a result, comments are a key feature of the platform, enabling significant influence with minimal effort. Active commenters represent only a small minority, and tend to hold more extreme views than the "silent majority" (Bail 2022). Moreover, it has repeatedly been shown that comments influence readers in their perception of a video (Walther et al. 2010; Hsueh, Yogeeswaran, and Malinen 2015; Searles, Spencer, and Duru 2020). The use of social media by politicians and the engagement they generate have been previously studied in a variety of contexts and from different research perspectives, from computer science to political science (Rajapaksha, Farahbakhsh, and Crespi 2024; Boulianne and Larsson 2023; Peng 2021; Möller et al. 2019; Engesser et al. 2017). Likewise, relationships between user bases of news media accounts of diverse political leanings have previously been explored (Wu and Resnick 2021; Cage, Herve, and Mazoyer 2020; Cointet et al. 2021). However, the vast majority of previous research focuses on the US context, which is bipartite, whereas the French political landscape is multiparty, with the last two presidential runner-ups not belonging to traditional left-wing or right-wing parties.

In this study, we broaden the scope of analysis to include both politicians/political parties channels (later referred to as PP channels), and news media channels (later referred to as NM channels). We ground our work in a highly intense election period in France, during which two distinct elections were held within four weeks, comprising a total of three rounds of voting, one of which concluded with the victory of a far-right party. We chose to focus on the YouTube platform as 61% of French people use it weekly, with 56% of them turning to it specifically to get informed (Reech 2025). We also account for recent developments on the YouTube platform, particularly the introduction of short-form videos in 2021 under the term *Shorts* (Sherman 2021), and observe the diverse and unevenly successful uses of this new format. To better characterize this unprecedented situation, we further compare our results with previous elections data.

This work is organized around two main axes of interest. First, we explore how NM and PP channels use the YouTube platform during the French European and legislative elections, as well as the reception from their audiences. To this end, we provide a novel characterization of channels within the French political-media ecosystem, encompassing both NM and PP YouTube channels. We analyze their uploading activity and the structure of their commenting user base, highlighting differences based on channel type and political orientation. The second axis of research focuses on the relationship between NM and PP channels, particularly the overlap of their respective commenting audiences, and the editorial choice made by NM channels regarding which political guests are shown on YouTube. We divide these two axes of investigation into the four research questions below.

RQ1 What characterizes NM and PP channels in terms of uploading behavior, and how can it be linked to the political orientation of the channels?

RQ2 How do audience engagement patterns (views, likes, and commenters behavior) differ between NM and PP channels?

RQ3 What are the relationships between the commenting user bases of PP channels, and how do these relate to those of NM channels?

RQ4 Which politicians appear on NM channels, and how does this affect the commenting user base?

To explore these questions, we analyze YouTube channels of the main French news outlets and the main French politicians and parties. We collected channel information, video metadata and comments of 35 NM channels and 29 PP channels, over a four-month period that included the French European elections and the subsequent legislative elections, resulting in a dataset of 43.5k videos, and 7.4M comments. We also collected videos of the same channels posted during previous French legislative elections, in June 2017, obtaining 28.4k additional videos, to observe the evolution of channels' practices over the years. We describe channels by analyzing their upload and engagement metrics, and their commenting communities using three different graph representations: a bipartite video-commenter graph, a commenter-projected graph, and a novel combination of the two. We also used pre-trained LLMs to investigate the presence of politicians in NM channel videos and how this affected the overall commenting network.

Our results highlight a different usage of YouTube, and a different reception from its audience, according to political orientation and channel type (NM versus PP). We show a conditional effect of Shorts, benefiting only channels with an already strong user base, and that PP left-wing and far-right channels attract more engagement. Additionally, our network analysis shows that PP left-wing and far-right channels also foster tighter, more clustered communities of commenters. We also evaluate the proportion of commenters interacting with both NM and PP channels, and/or commenting on politically opposite channels, and find a core of very active, cross-commenting users. Finally, we reveal that far-right politicians were increasingly featured in center- and right-leaning NM channels and that when politicians were discussed or featured in NM channel videos, the overlap between the NM channel's commenters and commenters from PP channels increased significantly, regardless of the orientation of the politicians.

2 Related Work

Social network analysis approaches. At the early stages of YouTube, Cheng, Dale, and Liu (2008) provided a large-scale analysis of the platform, using data from over 3 million videos. They explored YouTube items' statistical properties, such as video length, engagement metric evolution, and popularity distribution, and its network characteristics, showing the small-world characteristics (Travers and Milgram 1969) exhibited by the platform, extending results of Mislove et al. (2007) on online social networks to YouTube. Wattenhofer, Wattenhofer, and Zhu (2012) had access to the complete YouTube subscription graph and comment graph. Using graph-based methods, they examined social interaction and popularity on the platform and compared them with other popular online social networks. They revealed that popularity (number of subscribers) was better correlated with the popularity of one's most successful content rather than with the summary measures of content popularity.

Previous work on commenter influence includes O'Callaghan et al. (2012), who constructed a co-commenter network based on comment similarity and detected spam bots using network analysis methods. They discovered that these bots' comments were frequently linked to coordinated campaigns targeting multiple videos and spanning over extended periods. The collective influence of groups of commenters was also analyzed by Alassad, Agarwal, and Hussain (2019), who proposed a new method to identify coordinated commenter behavior and showed that these coordinating groups have significantly higher interacting/influencing power than other communities. Shajari, Alassad, and Agarwal (2023) categorized channels based on the commenting patterns they exhibited and revealed common patterns associated with suspicious behavior. Byun, Jang, and Baek (2023) showed how video engagement was impacted by a video creator commenting their video or answering comments, using a hierarchical regression analysis.

Cross-commenting and in-group commenting patterns have been explored, especially on Twitter/X, until recently, where Çetinkaya et al. (2025) showed that cross-partisan interactions persist on Twitter and vary by topic, revealing where toxicity concentrates. Focusing on YouTube, Wu and Resnick (2021) analyzed comments posted under US news channels, evaluated the political partisanship of commenters, and showed that cross-commenters were not unusual but were more toxic than in-group commenters. Focusing on French media websites, Cointet et al. (2021) identified structural features of their hyperlink network and concluded that the French media ecosystem did not suffer from the same level of polarization as in the US.

Elections and social media commenters. Commenter behavior in the context of elections has already motivated a large body of research. Nizzoli et al. (2021) uncovered coordinated behavior on Twitter around the 2019 UK General Election 2021. Covering the same election, and also on Twitter, Hristakieva et al. (2022) proposed an alternative method to discover propaganda operation and coordinated behavior, and evaluated its impact and influence. Peeters et al. (2023) studied the engagement Belgian politicians' posts received on Facebook around elections. Chen and Wang (2022) analyzed comments posted on YouTube under misinformation-based political advertisements around the 2020 US election. Flamino et al. (2023) compared the volume of biased political content between two US presidential elections (2016 and 2020) and observed an increase in online polarization. Finally, Sosnovik, Violot, and Humbert (2025) also focused on the 2024 French elections period and conducted an in-depth analysis of the different topics discussed by the political and news media actors on YouTube during that period.

Contrary to previous work on YouTube comments around election times, we focus on the network dynamics of commenters rather than on comment content, and we incorporate both NM and PP channels together, in the French context.

3 Data Collection and Processing

News media channel choice. We collected a list from the CSA[1] of TV and radio channels that invite politicians and cover political news (CSA 2024), to which we added the main French daily newspapers and weekly magazines that cover political and societal news from a list produced by the ACPM (ACPM 2024).[2] Finally, we added two "pure players", Blast and Le Média, which have a strong presence online. Not all NM were present on YouTube, and we obtained a final list of 35 channels.

Politician and party channel choice. We identified 13 parties using the list of the 2024 European election results (Schumann 2024) and the list of legislative campaign candidates (Ministry of the Interior 2024). To this list, we added the heads of parties and the heads of European lists. We then searched for active YouTube channels of identified politicians and parties, and obtained 29 channels in total.

Grouping the channels. In some parts of the analysis, for ease of comprehension and visualization, we grouped channels based on their political orientation. For PP channels, we grouped all channels belonging to the same party together, and further grouped parties by their political orientation—far-left, left, centrist, right, and far-right—as given by the *Ministry of the Interior and Overseas Territories*.[3] For NM channels the grouping was more challenging, considering the fact that political bias attribution is a complicated and subjective task. We started our classification by referencing Media Bias/Fact Check[4] and Eurotopics[5], using the simplified categories *right*, *center*, and *left*. Some outlets were not mentioned in our sources, and some had a recent change in ownership or editorial alignments. These were independently labeled by two annotators, using the same methodology as Media Bias/Fact Check, and later discussed until full agreement. Final orientations are given in Tables 3 5 in the appendix.

Channel, video, and comment collection. We set our collection period from March 1st, 2024, to July 14th, 2024 covering more than three months before the European elections to a week after the second round of the French legislative elections. Using the YouTube API (YouTube Developers 2023), we collected channel metadata, all videos they posted during our period of interest, and all comments posted on these videos, for a total of 43.5k videos and 7.4M comments from 700k commenters. We further collected videos from the 2017 legislative election (11th and 18th June) campaign, to evaluate the evolution of the channels. We defined a collection window of the same number of days as our main collection, ending one week after the second round of the legislative election. Because the 2017 legislative elections occurred two months after the presidential election, this window includes a portion of the 2017 presidential campaign, making it a comparably intensive election period to our main period of interest. The YouTube API imposes a limit of 20k videos when collecting videos from a channel using the upload playlist, and is not suited to collect videos older than a few months through the *search* endpoint (Efstratiou 2025). As some channels have uploaded more than 20k videos since 2017, we used the `yt_dlp` (yt dlp 2025) library to collect 2017 videos from this set of channels.

4 Methods and Definitions

4.1 Shorts Labeling

Shorts are an alternative format to regular videos (RVs) on YouTube, consisting of videos under 1 minute (at the time of the collect), in a square or vertical format. They are shown to users in a dedicated tab, in which users can scroll down Shorts, without actively choosing which Short they want to see next. Following the method from Violot et al. (2024), we classified videos between Shorts and RVs by sending a request to `youtube.com/shorts/<videoid>` for each video ID in our dataset and checked if "/shorts/" was in the URL response (meaning the video was a Short) or had been removed from the response (meaning the video was not a Short).

[1]The Conseil Supérieur de l'Audiovisuel (CSA), now Arcom, is the French authority in charge of regulating TV and radio channels.

[2]Alliance pour les Chiffres de la Presse et des Médias.

[3]www.legifrance.gouv.fr/circulaire/id/45472

[4]mediabiasfactcheck.com/

[5]eurotopics.net/

4.2 Graph Representations

Bipartite graphs and projected graphs. A bipartite graph $B(U, V, E)$ is a graph where U and V are two disjoint sets of nodes and E is the set of edges such that each edge $e \in E$ connects a node in U to a node in V, but no edge exists between two nodes in U or two nodes in V. From $B(U, V, E)$, we can extract the U-projected graph (or the V-projected graph). These projected graphs consist of nodes from U (resp. V), where edges are created between nodes if they share a common neighbor from V (resp. U).

As part of this study, we represent each channel by its bipartite **video-commenter graph** (VCG), with edges connecting commenters to videos they commented. We further construct the **commenter-projected weighted graph** (CPWG). In this graph, commenter nodes are connected if they commented on the same video(s). Edges in the CPWG are weighted based on the number of common videos co-commented by the two commenters.

We also represent whole channels and their associated commenters by a channel-commenter bipartite graph, with edges connecting commenters to the channels whose videos they commented on. We then construct the **channel-projected weighted graph** (ChWPG), where channel nodes are connected if they share at least one commenter. The weight of each edge represents the Jaccard similarity between the commenting sets of the two channels, that is, the fraction of common commenters out of all the two channels' commenters.

Augmented channel bipartite graphs. For each channel, we further combined the VCG and CPWG, using only edges with a weight ≥ 2 to construct the **augmented video-commenter graph** (AVCG). This graph connects videos to commenters, as well as commenters who co-commented on several videos from the channel, allowing us to identify strong community patterns. Figure 1 shows the bipartite graph of a channel and its corresponding AVCG.

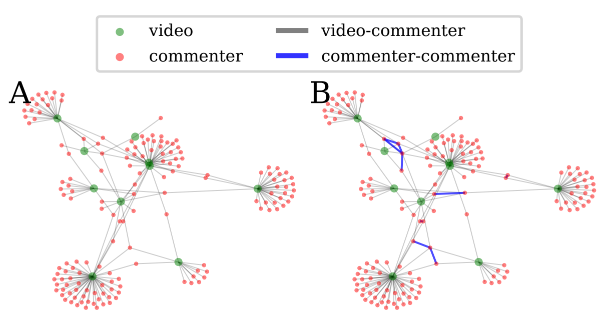

Figure 1: Example of an AVCG, using the videos and commenters from the channel "Les Républicains". **A** shows the bipartite network with videos and commenters, and an edge when a commenter commented on a video. **B** shows the same network with added edges between commenters if they co-commented on at least two videos from the channel.

4.3 Graph Measures

Let $G = (V, E)$ be a connected graph, where V is the set of vertices and E is the set of edges. The ***density*** of G is given by $D(G) = \frac{2|E|}{|V|(|V|-1)}$ and measures how full a graph is, that is, how many edges it has in comparison to the maximum number of edges it could have. The ***transitivity*** measures the likelihood that two nodes connected to a common neighbor will also be connected together. It is given by $t = \frac{|\{triangles\}|}{|\{triplets\}|}$, where a triplet is a set of three nodes with at least two distinct edges, and a *triangle* is a set of three mutually connected nodes. High transitivity indicates tightly clustered groups. The ***diameter*** of G, denoted $diam(G)$, is given by $diam(G) = \max_{u,v \in V} d(u, v)$, where $d(u, v)$ represents the geodesic distance (i.e., the length of the shortest path) between nodes u and v. A small diameter indicates a tightly interconnected structure.

Density bias. In our experiments, for each channel, we compute the densities of the VCG, AVCG, and CPWG. Each density measure introduces distinct biases, but together they offer a nuanced description of the channels under study. The VCG density is upper-bounded by the product between the number of videos and the number of comments and inherently favors graphs where these quantities are evenly balanced. The AVCG density is lower bounded by the channel's VCG density but also takes into account the proportion of commenters who co-commented on at least two videos from that channel. The difference between these two densities serves as an indicator of the commenters community cohesion. Finally, the CPWG density is biased towards channels with a low number of videos, reaching its theoretical maximum of 1 in the extreme case of a single-video channel. Therefore, the UDI party channel, which only had 10 comments, was removed from our results.

4.4 Politician Presence in News Media Videos

Using party official websites, party lists from current elections, and journalistic news for up-to-date information, we curated a list of 1213 current politicians from all parties. We then used pre-trained LLMs to accomplish two tasks; *mention extraction* and *interviewee extraction*, to infer which politicians were talked about and which were invited on NM channels.

Mention extraction. To identify mentions of politicians in video titles, we relied on a pre-trained CamemBERT model fine-tuned for named-entity recognition (NER), namely camembert-ner (Polle 2021; Martin et al. 2020), available through the HuggingFace Transformers library. The model was downloaded and executed locally on a standard workstation (Apple M1 Pro, 16 GB RAM). Each video title was processed individually through the model using the HuggingFace NER pipeline with simple aggregation, which returns entities grouped by category. From the output, we retained only the entities classified as persons. According to the model's documentation, this category achieves a precision of 0.94, a recall of 0.96, and an F1-score of 0.95, which supports the reliability of the extracted mentions.

Interviewee extraction. To identify who was speaking in the videos, we concatenated each video title and description into a single text input using the format: `"Title: <video title>\nDescription: <video description>"`. This input was then fed to an LLM with explicit instructions to extract only the names of speakers, excluding individuals who were merely mentioned (the complete prompt is available in the appendix). We compared the extracted names to our curated list of politicians and kept only those that corresponded to political figures. We evaluated four models: GPT-4o (OpenAI 2024b), GPT-4o-mini (OpenAI 2024a), Google's `flan-t5-base` (Google 2022), and `Mistral-Small-24B-Instruct-2501` (MistralAI 2025), all run with a temperature of 0 and a maximum output length of 40 tokens. GPT models were accessed through OpenAI's API, while `flan-t5-base` and `Mistral-Small` were downloaded from HuggingFace and executed on an NVIDIA A100 GPU node. To compare the models, we manually annotated 200 randomly selected videos and identified the politicians interviewed. Among tested models, `Mistral-Small` performed the best, with a precision of 0.78, a recall of 0.82 and an F1-score of 0.80. Table 2 in the appendix presents comparative performance data.

5 Results

5.1 Upload and Engagement Metrics (RQ1&2)

We began our analysis by examining how channels of different types and political orientations used YouTube during the 2024 elections period, and how audiences responded in terms of engagement. Table 1 reports the number of NM and PP channels by orientation, along with their upload and engagement metrics. Detailed results for individual channels are provided in the appendix. To place these results in context, we also traced the evolution of uploads and views between 2017 and 2024. For each channel and election period, we calculated the total number of uploaded videos and the average number of views, and then plotted the empirical complementary cumulative distribution functions (CCDFs) of each metric by channel type and orientation (Figure 2).

Upload metrics. Table 1 shows that both center and right-leaning NM channels were similarly very active, with nearly 10 videos per day on average, while left-leaning NM channels' upload activity was closer to PP channels than to other NM channels. The disparity in upload activity reflects distinct ways of using YouTube. First, when it comes to NM channels, there are two types to consider: (1) channels affiliated with TV/radio channels and (2) channels associated with the printed (online) press. The vast majority of videos posted by channels in the first category are snippets from television or radio broadcasts, while videos from channels in the second category are only intended for social media. In our dataset, centrist and right-leaning NM channels are primarily in group 1, whereas left-leaning NM channels are solely in group 2, which explains the lower upload number.

Looking at the upload activity evolution in Figure 2, we can confirm that the majority of center- and right-leaning

	# chan.	# vid. /day /chan.	Shorts (%)	views /vid.	likes /vid.	comm. /vid.
Left NM	4	1.44	25.2	123k	4.7k	713
Center NM	**18**	9.36	12.5	35.7k	526	150
Right NM	13	**9.95**	28.7	55.9k	1.0k	258
Far Left PP	2	0.43	1.30	6.5k	383	93.1
Left PP	11	0.86	31.1	96.3k	4.5k	571
Center PP	4	0.26	16.6	25.3k	469	246
Right PP	4	0.47	23.6	64.9k	4.3k	480
Far Right PP	7	0.77	**43.5**	**138k**	**7.6k**	**1.1k**

Table 1: Collection of **channels upload metrics** (number of videos per day per channel, percentage of Shorts) and **engagement metrics** (views/video, likes/video, and comments/video), grouped by orientation. Each metric was computed for every channel and averaged over channels of the same orientation.

NM channels posted over 1,000 videos in 2024. While center-leaning NM channels were already active in 2017, we can see that right-leaning NM channel activity has expanded significantly since 2017.

PP channels are less active, posting about one video every two days. Among them, left-wing and far-right channels were much more active, averaging 0.86 and 0.77 videos per day, compared to upload rates ranging from 0.26 to 0.47 for the other political orientations. This activity gap widened between 2017 and 2024 as both left-wing and far-right channels increased their production, with the far-right showing the most dramatic rise. In contrast, the activity of right-wing PP channels decreased.

Far-right and left-wing also post more Shorts than other orientations, especially far-right, whose channels had 43.5% Shorts on average, and where the main party (RN) had 98.6% Shorts. Among NM channels, the percentage of Shorts of left- and right-leaning channels is twice higher than that of center channels.

Engagement metrics. Engagement metrics analysis deserves a moderate dive into the French political landscape, to understand the diversity of audience responses among parties of the same orientation. Far-right channels lead in engagement, driven largely by the young leader of the main party (RN), J. Bardella. His channel, launched in 2019, averages over 310k views/video. The other main figure of the party, presidential candidate M. Le Pen also has a very popular channel (107k subscribers), while E. Zemmour and F. Philippot, even more radical figures, had respectively the channels with the highest number of commenters per video (1.9k) and the highest number of likes per video (16.4k). The left-wing group shows similarly high engagement, mainly due to the LFI party, founded in 2008 after splitting from the traditional left PS party. LFI leader J.-L. Mélenchon has 1.1M subscribers, by far the most of any PP channels (the second highest value was 511k at the time of collect), and around 308k views/video on average. In contrast, the traditional left-wing party (PS) channel averages just 3k views per video. Right-wing channels show relatively high engage-

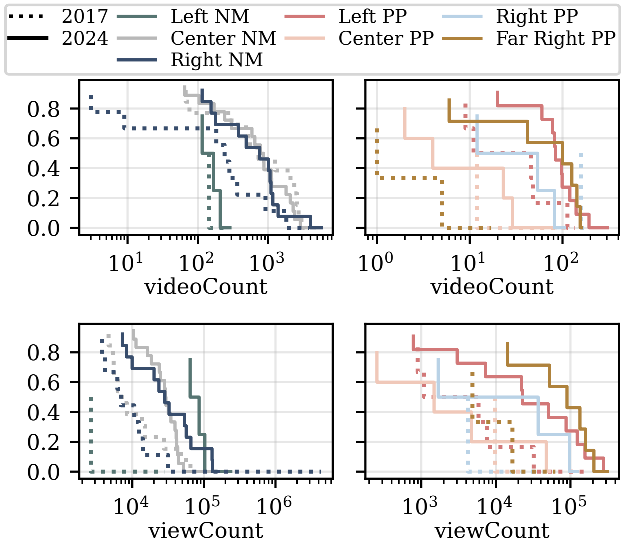

Figure 2: Empirical CCDFs of uploads and view counts, grouped by orientation. For each NM and PP orientation, we aggregated all videos from channels of that orientation and computed the distribution of uploads and view counts.

ment, with an average of 64.9k views per video. This is not due to the main party (LR), which only has a mean of 1.7k views per video, but due to an alternative right party, the UPR, with a mean of 110.6k views per videos, a party known for its active presence online, and its strong militant core (franceinfo 2019), and to a lesser degree the DLF party with 36.9k views per video. Far-left and centrist channels, except a relative success from president Macron's channel, show significantly lower engagement.

Therefore, it appears that for politicians, engagement on YouTube is not necessarily tied to legacy media presence, which confirms that the platform can be an effective way to reach an audience. Channels tied to high-profile leaders (Mélenchon, Bardella) attract disproportionate engagement. However, this is also true for politicians less covered or excluded from legacy media, such as F. Asselineau and his party UPR and F. Philippot and his party LP. We can see on Figure 2 that this clear superiority of left-wing and far-right parties in terms of user engagement is a fairly recent phenomenon. In 2017, engagement results were not as distinguishably in favor of the two orientations.

Concerning NM channels, left-wing channels have by far the most views, likes, and comments per video, followed by right-wing channels, and in last, center channels with 3.5× fewer views, 9.4× fewer likes and 4.7× fewer comments per video than left-wing channels. As previously stated, left-wing NM channels have their content tailored for and exclusive to social media, which can explain the higher engagement they generate.

Impact of Shorts. Shorts have been shown to generate higher engagement than RVs, both overall and within the same channel (Violot et al. 2024). To test whether this holds for French NM and PP channels, we compared the mean number of views in Shorts and RVs for each channel. We found completely diverging results among channels. For presidential party members (center), and the PS (left-wing), Shorts had a very negative effect, generating 2 to 10× fewer views than RVs. But for LFI (left-wing), RN (far-right), and UPR (right-wing) members, Shorts generated 10 to 15× more views. It appears that for popular channels, the use of Shorts had a positive effect, whereas for less popular channels, the effect was negative. We then computed the Pearson correlation between a channel's percentage of Shorts and its mean number of views (Shorts and RVs), finding a modest correlation of 0.59 (p = 0.001) for PP channels and none for NM channels (0.00, p = 0.99). This shows a subtle effect, where Shorts are either associated with more or fewer views than RVs within a given channel, and have a very limited effect on the overall popularity of the channel. As this result contradicts the general effect of Shorts given in Violot et al. (2024), a further investigation of what differentiates Shorts content across channels—NM and PP—would shed light on this mixed result.

In the light of upload metrics, engagement metrics and usage of Shorts, we observe an interesting pattern. Far-right groups, LFI, and non-traditional right groups appear to be more active and draw more engagement than other groups. All historically faced limited visibility in legacy media and social media provided them with an opportunity to reach audiences that were otherwise hard to reach. Thus, results align with the notion of media bypass by politicians seeking unmediated visibility (Kruikemeier, Gattermann, and Vliegenthart 2018). The media landscape has since shifted, with far-right politicians and LFI members now well established in mainstream outlets. However, their early adoption of social media, YouTube included, suggests a more flexible and effective use of the platform, shown by their activity and the disproportionate engagement they generate. In contrast, centrist actors tend to adhere to traditional media strategies. Beyond upload frequency, this is best exemplified by the use of Shorts, a social-media native format, well leveraged by the left and far-right, and overlooked by centrist channels.

5.2 Commenter Network Metrics (RQ2)

We now analyze commenter networks, depending on the types of channel (NM or PP) and their orientations. For each channel, we retrieved its bipartite video-commenter graph (VCG), computed its commenter-projected weighted graph (CPWG), and used the latter to add edges to the video-commenter graph between commenters who co-commented on more than one video, yielding the channel's AVCG. As metrics for comparing the different channel networks, we used the diameter, transitivity, and density of the AVCG, along with the densities of the VCG and CPWG. Results are shown in Figure 3.

From Figures 3(a) and 3(b), we observe that the diameter is smaller for PP channels ($\mu = 6.2$, $\sigma = 1.9$) than for NM channels ($\mu = 9.7$, $\sigma = 2.7$), and that the transitivity is generally higher for PP channels ($\mu = 0.28$, $\sigma = 0.13$) than NM channels ($\mu = 0.18$, $\sigma = 0.09$). Left-leaning NM channels

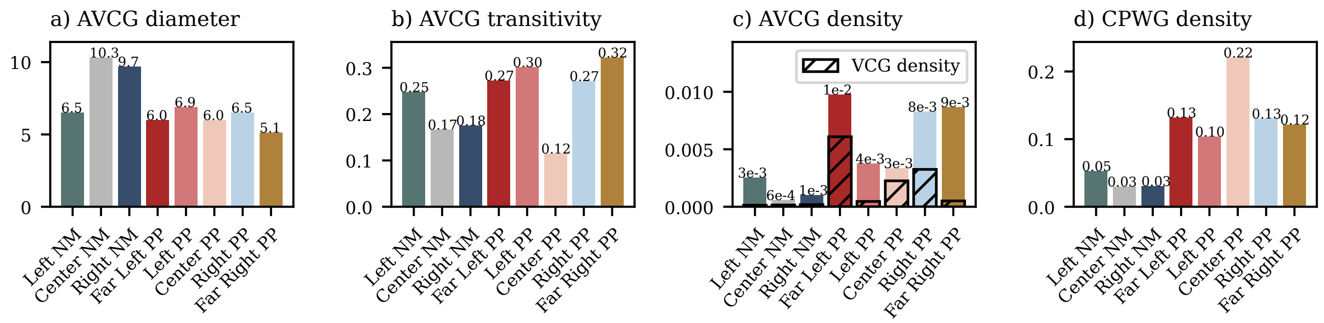

Figure 3: Network measures aggregated over channels' orientation. Each measure was computed for each channel and then averaged over channels of the same orientation.

are an exception, averaging a diameter of 6.5 and a transitivity of 0.25. Centrist PP channels have low transitivity on average (0.12), with the exception of President Macron's channel, which has a transitivity of 0.31. These two values indicate that PP channels act more like small worlds (Travers and Milgram 1969) than NM channels, with more clusters and closer commenters.

The VCG density, shown in Figure 3(c) in dashed bars, is the highest for far-left and right-wing PP channels, which both have a more balanced number of videos and commenters. When examining the AVCG density, also in Figure 3(c), we see that it is only 2× higher than the VCG density for these channels. In contrast, left-wing and far-right PP channels initially have low VCG densities. However, the AVCG density exhibits a substantial scaling effect—increasing by a factor of 17 for far-right channels and 8 for left-wing channels. If we remove the traditional left-wing PS party, the growth factor reaches 16 for left-wing channels.

As explained previously, a low number of videos can explain a high CPWG density, as shown in the case of center channels which have the lowest number of videos and therefore exhibit a very high density. The rest of the PP channel groups have similar CPWG densities, systematically higher than NM channel groups.

To conclude, in regards to all the network metrics, PP channels foster more strongly connected networks than NM channels, especially compared to center- and right-leaning NM channels, showing PP channels' ability to build communities, whereas NM channels are more porous and diverse. However, there are differences among channels based on orientation. For example, left-leaning NM channels' network metrics are closer to PP channels' than to other NM channels'. Conversely, centrist and right-wing PP channels exhibit weaker commenting communities than other PP channels, with less clusters and low VCG and AVCG densities, indicating a lack of a mobilized base. We can tie these loose networks to the low activity of centrist and traditional left-/right PP channels, shown in the previous section, but also to the likely low participation of their supporters, due to the profile of these party voters (IPSOS 2024) who rely more heavily on traditional media such as television and radio for political information, rather than social media (Bousquet, Figeac, and Neihouser 2024). These two factors lead to low politician and supporter participation on social media for centrist and traditional left/right parties.

5.3 Common Commenters (RQ3)

Shifting from the analysis and comparison of individual channels, we now examine how these channels might be interconnected through shared commenters.

Commenters activity. We begin this cross-channel analysis by evaluating the number of comments per commenter, dividing them into five groups: 1) only NM commenters, 2) only PP commenters, on same orientation channels, 3) only PP cross-orientation commenters who commented on PP channels of at least two distinct orientations, 4) Cross-type single-orientation commenters who commented on both NM and PP channels, of the same orientation, and 5) cross-type cross-orientation commenters, similar to group 4 but with PP channels of at least two distinct orientations.

We found 67% of only-NM commenters, with 4 comments per commenter on average; 10.7% of only-PP single-orientation commenters with 2 comments per user; 0.6% of only-PP cross-orientation commenters, with 5 comments per user; 14.8% of cross-type single-orientation commenters with 18 comments per user; and 6.9% of cross-type cross-orientation commenters with 70 comments per user.

Focusing on commenters who commented on at least one PP video, we found that 33.0% commented only on left channels, 48.3% commented only on right channels, and 15.2% commented on both, the remaining part consisting of commenters who also commented on center channels. We see that, while the percentage of commenters engaging with channels of two different orientations is relatively low compared to those interacting exclusively with same-orientation channels, it remains a non-negligible portion.

Percentage of common commenters. Again grouping channels by type (PP vs. NM) and orientation, we examine the commenter overlap across these groups. For each group, we identify commenters who commented at least once on channels from that group and compute the percentage who

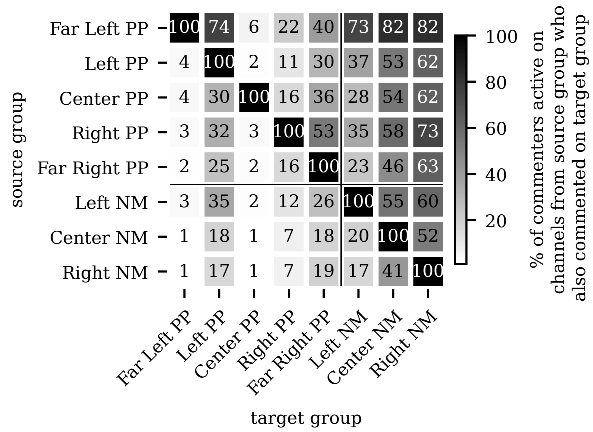

Figure 4: Percentage of commenters who commented on videos from channels in the y-axis group who also commented on videos from the x-axis group. Commenters are counted as part of a group if they commented at least once on any channel in that group.

also commented on other groups' videos. Figure 4 presents these percentages in the form of a heatmap.

We confirm that those who comment on PP channels also largely comment on NM channels, as shown by the high values of NM channels columns [23-82%], whereas the opposite is not true, with a majority of values $< 15\%$ on PP channels columns. Right-leaning NM channels, and to a lesser degree center-leaning ones, attract particularly large portions [52-82%] of commenters from all orientations. Left-leaning NM channels report lower values, which is expected given the much lower volume of uploads compared to other orientations. Among PP groups, left-wing and far-right channels receive a large share of commenters from other groups. We see that commentors from far-left channels are also extremely active on most other groups [6-82%]. A majority (53%) of commenters from right-wing channels also comment on far-right ones.

Political channels network. We then move to the analysis of the channel-projected weighted graphs, first focusing only on PP channels. The density of the PP ChPWG was 0.977, indicating that almost all PP channels shared at least one commenter. Figure 5 shows the 25 highest Jaccard similarities between channels' commenters.

We observe that channels with the same orientation are often strongly connected, except for centrist channels which do not appear in our top edges. One notable exception is the strong Jaccard similarity between M. Le Pen (far-right) and the PCF (left-wing). Upon investigation, we discovered several profiles of commenters. Some defend either left, either right/far-right ideas, some defend both, or some defend other parties. We translated some examples below:

From a presumed left-wing commenter:
- on PCF videos: *"Support all left candidates."*
- on M. Le Pen videos: *"L00SERS"* (untranslated)

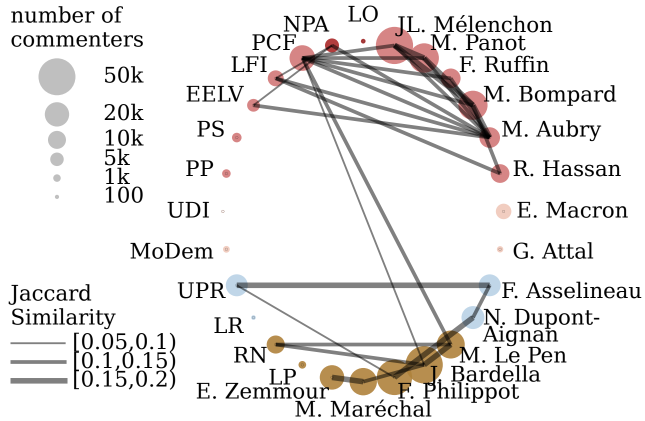

Figure 5: ChPWG of all PP channels in our dataset, with weighted edge between the 25 pairs with highest Jaccard similarities between channels' commenters.

From a presumed right-wing commenter:
- on PCF videos: *"The left in all its splendor."*
- on M. Le Pen videos: *"No mercy, no forgiveness for those who don't vote RN on July 7."*

From a presumed troll:
- On PCF video mentioning RN: *"I express my solidarity and total support to any populist movement"*
- On M. Le Pen videos: *"Let's mobilize again for the victory of the RN"*
- Also on M. Le Pen videos: *"Mobilize against the RN!"*

Political-News channels network. We then examine the relationships between NM channels and PP channels, using all channels to create the ChWPG. The density of the obtained graph is 0.994. Our goal was to highlight interactions between NM channels and PP channels, so we removed links connecting channels of the same type (i.e., links between two NM channels or two PP channels).

Figure 6 displays the Jaccard similarity among the 30 most similar channel pairs. We observe that, in contrast with Figure 5, based only on PP channels, the size of NM channels has less impact on the number of strong edges. For example, while being relatively smaller in number of distinct commenters, the *franceinfo* channel and the *L'Humanité* channel have stronger edges than some larger channels, such as *France 24* or *BFMTV*. We also notice many strong edges connecting left-wing PP channels and NM channels from all political orientations, especially right-leaning NM, confirming earlier results. This effect is unrelated to channels commenters count, as illustrated by M. Bompard's (left) high edge count despite far fewer commenters than far-right figures like J. Bardella or F. Philippot. Additionally, and similarly to results from Figure 5, we observe a strong edge between M. Le Pen and the NM channel L'Humanité which is close to the PCF party.

Hence, what we can refer to as *commenting echo chambers*—commenting mainly within a given political group/orientation—coexists with cross-posting. While commenters often stick to ideologically aligned channels, we

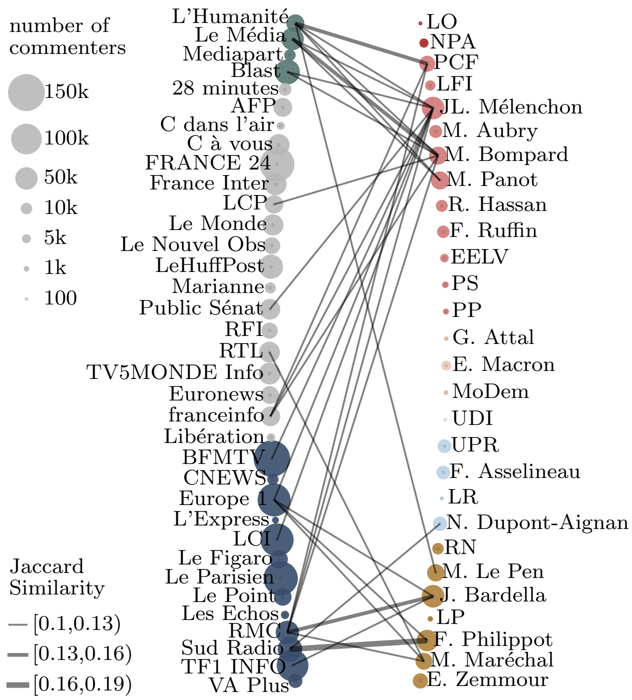

Figure 6: ChPWG of all channels showing the 30 edges with the highest Jaccard similarity. Edges between channels of the same type (NM or PP) were removed.

show a non-negligible crossover between channels of opposite orientations. This supports a hybrid commenting behavior, where users comment inside partisan spaces but also interact with oppositional content. Our observations, confirmed by prior research (Wu and Resnick 2021), suggest that such interactions often include disagreement or trolling. Importantly, those who engage across political lines are not typical users; they are highly active commenters, far more prolific than the average. Therefore, cross-posting behavior does not undermine the idea of echo chambers' narratives which persists for most users. It rather supports a political agency of these users, as previously pointed out (Khan 2017), willing to devote effort to offering their agreement, disagreement, or nuance to the content in the videos.

5.4 News Channels Coverage of Politicians (RQ4)

Our last collection of results concerns the presence of politicians in NM channels' videos and its impact on commenters.

Who's featured? We begin by investigating the distribution of political orientations among politicians mentioned or appearing on NM channels. For each NM video, we applied the Named Entity Recognition (NER) task and the interviewee extraction task, described in Section 4, to identify politicians who were mentioned or appeared in the video, to match them to their political orientation. Videos were then grouped by the orientation of their channel, allowing us to estimate the share of mentions or appearances for each political orientation. This procedure was repeated for both election periods, with results shown in Figure 7. For 2017,

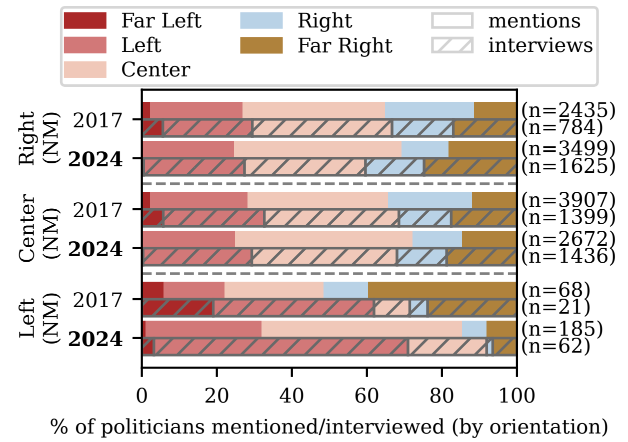

Figure 7: Political orientation of politicians mentioned or interviewed in NM videos, grouped by NM channel orientations and year, showing the evolution of politicians featured between 2017 and 2024.

we excluded videos published between the two presidential rounds to avoid bias from the disproportionate visibility of the two runner-ups and their allies, whose media presence reflected first-round results rather than NM editorial choices.

First, focusing on the 2024 results, we see strong similarities between center- and right-leaning NM. Both mainly highlight centrist politicians, followed by left-wing and far-right figures, while right-wing politicians receive less attention and the far left is absent. Centrist politicians dominate mentions across both types of channels, though their prominence decreases in interviews, especially on right-leaning NM where they are outnumbered by right and far-right figures combined. By contrast, 75% of the guests on left-leaning media are from the left, including a few from the far left. Figures from the right and far-right were occasionally mentioned, but almost never featured in interviews. When that is the case, it is always from "second-hand interviews", where extracts of interviews from other media are shared and commented. Centrist politicians are rarely interviewed but are often mentioned.

Comparing with 2017, we first notice that right-leaning channels doubled the number of political interviews uploaded between 2017 and 2024. Over the same period, the share of far-right mentions and interviews increased impressively, going from 12% (resp. 17%) to 15% (resp. 19%) in center NM and from 11% (resp. 17%) to 18% (resp. 25%) in right-leaning NM. On left NM channels, the opposite holds, with far-right politicians being overly mentioned and shown (from second-hand interviews) in 2017, by the only active left NM channel of our dataset at the time. The share of far-right politicians then dropped between 2017 and 2024, mostly to the benefit of centrist politicians. During both election periods, politicians on the left were largely predominant. Finally, we can see the coverage of far-left politicians decreasing for left-leaning NM, and disappearing in center- and right-leaning channels in 2024.

Therefore, it appears that there is a clear distinction between which politicians are named and which are interviewed in the videos posted by the various NM channels. Notably, far-left politicians are absent from center- and right-leaning NM channels, but the same channels do not show the same restraint with far-right politicians, who are frequently mentioned and interviewed. Conversely, left-leaning NM channels exhibit the inverse bias: they mainly mention and interview politicians from left-wing groups, and while far-right figures are often discussed, they are not invited. This dual phenomenon reveals a form of editorial gate-keeping in which channels selectively promote certain political actors while marginalizing others.

An important nuance is that not all NM outlets operate under the same constraints. At first glance, left-leaning NM channels could appear more partisan than right-leaning ones. But in reality, right-leaning and center NM are, for the most part, radio and TV broadcasters available on the FM band and TNT (terrestrial television) and are subject to certain obligations to pluralism in exchange for access to a broad audience. Hence, the growing share of far-right politicians on right-leaning and center channels, and the disappearance of far-left politicians, can have a significant impact on the general public. This contrasts with the online-only presence of left-leaning outlets which typically reach self-selected, ideologically aligned users (Bousquet, Figeac, and Neihouser 2024) but enjoy more freedom in their choice of guests.

Impact of politician presence on commenters. We examine how the mention or presence of politicians in an NM video changed its commenting user base. To do this, we initially split videos based on whether a politician was mentioned. For each NM channel, we compare the number of commenters on videos from the two groups, and found that, on average across channels, videos featuring a politician attracted 1.86× more commenters than those without.

To better understand the origins of these commenters, we further classified the videos of each NM channel into three categories: (1) no politicians interviewed, (2) any politician interviewed, and (3) politicians from a specific political orientation interviewed. This gives us seven subsets of videos per channel: one for category (1), one for category (2) and five for category (3), one for each possible orientation of the politician being interviewed. For each video subset we extracted the corresponding set of commenters which commented on a video from that subset. We therefore obtain seven commenter sets: $\mathsf{com}_{\mathsf{NM,no\,polit}}$ for group (1), $\mathsf{com}_{\mathsf{NM,any\,polit}}$ for group (2), and, for each orientation o in group (3), $\mathsf{com}_{\mathsf{NM,polit\,from\,o}}$.

We also grouped PP videos by their political orientation and, for each orientation o, extracted the complete set of commenters who engaged with those videos, denoted $\mathsf{com}_{\mathsf{PP,o}}$. For each NM channel and each PP orientation, we then computed the percentage of commenters from each set $\mathsf{com}_{\mathsf{NM,c}}$, where $\mathsf{c} \in [\mathsf{no\,polit}, \mathsf{any\,polit}, \mathsf{polit\,from\,o}]$, that also belonged to $\mathsf{com}_{\mathsf{PP,o}}$. In particular, we focused on the percentage of commenters from sets $\mathsf{com}_{\mathsf{NM,o}}$, who also commented videos of politicians from the same orientation. Finally, we averaged these percentages over all NM channels

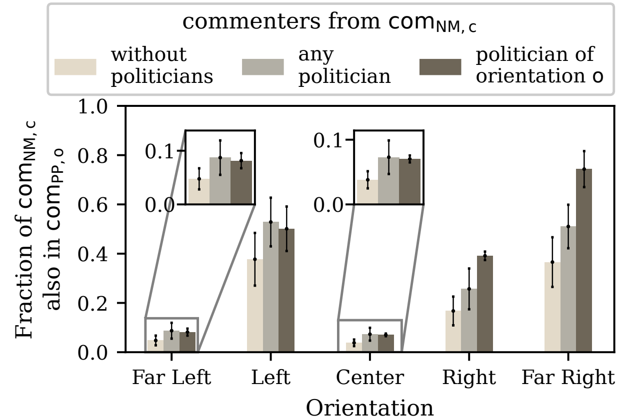

Figure 8: Impact of politician presence in NM videos on audience overlap with PP channels. For each channel and for each category c of NM videos (no politician, any politician, and specific orientation o), we show the average percentage of commenters in that category ($\mathsf{com}_{\mathsf{NM,c}}$) who also commented on PP videos ($\in \mathsf{com}_{\mathsf{PP,o}}$). Results are shown separately for overlaps with PP channels of the same orientation and of different orientations.

and obtain the results shown in Figure 8.

First, looking at the effect of politician presence without taking their orientation into account, we observe that a politician's presence in a video greatly increases the fraction of commenters who also commented on PP videos, of any orientation. For example, for NM videos without politicians, on average, 4.8% of commenters also commented on videos from far-left PP channels, but for NM videos with a politician this percentage increases to 8.7%. This holds when looking at the specific orientation of the politician being interviewed, the percentage of commenters also in $\mathsf{com}_{\mathsf{PP,orientation}^i}$ increases with the presence of a politician with the corresponding orientation. For far-left, left, and center, the orientation of the politician does not cause a big difference in the percentage of commenters also in $\mathsf{com}_{\mathsf{PP,orientation}^i}$. For right and far-right the percentage of commenters also in $\mathsf{com}_{\mathsf{PP,orientation}^i}$ increases significantly when the politician interviewed is from their corresponding orientation, jumping from 25% to 40% for right-wing politicians compared to other orientations and from 51% to 74% for far-right politicians.

Therefore, politician presence acts as a bridge between PP and NM channels. When an NM channel video features a politician, the percentage of its commenters who also comment on videos from politicians of the same orientation as the one shown in the video increases considerably, especially for right and far-right politicians. Additionally, videos featuring a politician of any orientation increase the presence of commenters from all groups. This, together with the previously observed cross-commenting activity, supports the theory of commenters as politically invested actors, going beyond PP channels to support or contradict politicians, and following them into NM channels to express their opinions.

6 Conclusion

In this article, we examined the different ways in which political actors and news media in France used YouTube during a highly active electoral period. We found that activity and engagement differ significantly among orientations and across NM and PP channels. During these campaign periods, left-wing and far-right channels were far more active and engaging than centrist and traditional right-wing channels. They also made a greater usage of Shorts. Left-leaning NM channels were less active but received far higher engagement than center- and right-leaning ones. One striking result is the conditional impact of Shorts which led to higher engagement only for already popular PP channels. Diving deeper into Shorts dynamics and their impact on political communication is a promising direction for future research.

Regarding commenting patterns, PP channels had tighter, more coherent commenting communities than NM channels, especially on the left and far-right. Centrist channels showed weaker communities. While commenters often remain inside ideologically aligned spaces, cross-orientation commenters were present and prolific, suggesting motivated political engagement, not random exposure.

We also showed that NM channels favor politicians with similar political leanings in their coverage and interviews, a phenomenon that intensified over the years. Left-leaning channels rarely featured far-right figures and mentioned them less and less, while center- and right-leaning channels stopped featuring far-left politicians and increasingly interviewed and mentioned far-right politicians. In general, centrist politicians were overrepresented, at least in mentions, across all NM orientations. Regarding commenting behavior, we found that the presence of politicians in NM channels' videos significantly increased commenters overlap between PP and NM channels, not only between aligned channels but all across the political spectrum.

As a final remark, we notice that far-right politicians not only make effective use of YouTube in their uploading habits as well as in audience response, they also benefit from a growing share of NM videos mentioning or featuring them, from right-leaning and centrist channels. We cannot attribute their victory in the French European election to their YouTube presence only, but, considering the growing number of potential French voters who use YouTube as a source of political information, its effect should not be underestimated either. Additionally, for TV and radio NM, YouTube is a way to re-publish their content, after a broadcast on their medium of origin, doubling the exposure of invited politicians and extending their reach to new audiences (IPSOS 2024). Legacy media have been increasingly criticized for mainstreaming far-right ideologies (Plottu and Macé 2024), and YouTube appears to function as yet another vector through which these narratives are reinforced and normalized within the public sphere.

Limitations. This study deliberately centers on the French political-media ecosystem to move beyond the predominantly US-centric focus of prior research. While offering diversity, our findings are similarly context-specific. We focused on YouTube, but a cross-platform analysis, including social media targeting different demographics such as X, Facebook, and TikTok, could provide a more holistic view of how politicians and news media engage online. Finally, the political orientation of NM channels was in part manually annotated, based on external references and annotator judgment, which introduces a degree of subjectivity.

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1. For most authors...
   (a) Would answering this research question advance science without violating social contracts, such as violating privacy norms, perpetuating unfair profiling, exacerbating the socio-economic divide, or implying disrespect to societies or cultures? Yes
   (b) Do your main claims in the abstract and introduction accurately reflect the paper's contributions and scope? Yes
   (c) Do you clarify how the proposed methodological approach is appropriate for the claims made? Yes
   (d) Do you clarify what are possible artifacts in the data used, given population-specific distributions? Yes, it specifies several times that we focus on French political-media ecosystem and make no claim that our findings can be generalized to other countries.
   (e) Did you describe the limitations of your work? Yes, in a dedicated section in the conclusion
   (f) Did you discuss any potential negative societal impacts of your work? Our work is mostly descriptive, does not provide any means to any actors, hence has limited to no negative societal impact.
   (g) Did you discuss any potential misuse of your work? No, but as mentioned in the previous question the potential negative societal impact is very limited as it's a descriptive article, and we don't offer a model, nor disclose any sensitive data.
   (h) Did you describe steps taken to prevent or mitigate potential negative outcomes of the research, such as data and model documentation, data anonymization, responsible release, access control, and the reproducibility of findings? No, same answer than previous question.
   (i) Have you read the ethics review guidelines and ensured that your paper conforms to them? Yes
2. Additionally, if your study involves hypotheses testing...
   (a) Did you clearly state the assumptions underlying all theoretical results? Yes
   (b) Have you provided justifications for all theoretical results? Yes
   (c) Did you discuss competing hypotheses or theories that might challenge or complement your theoretical results? Yes
   (d) Have you considered alternative mechanisms or explanations that might account for the same outcomes observed in your study? Yes
   (e) Did you address potential biases or limitations in your theoretical framework? Yes
   (f) Have you related your theoretical results to the existing literature in social science? Yes
   (g) Did you discuss the implications of your theoretical results for policy, practice, or further research in the social science domain? Yes
3. Additionally, if you are including theoretical proofs...
   (a) Did you state the full set of assumptions of all theoretical results? NA
   (b) Did you include complete proofs of all theoretical results? NA
4. Additionally, if you ran machine learning experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? Yes
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? Yes
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? No, the core of the article is not models performance so we did not run the experiment multiple times.
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? No, the model was pre-trained, easy to run on a personnal machine.
   (e) Do you justify how the proposed evaluation is sufficient and appropriate to the claims made? Yes
   (f) Do you discuss what is "the cost" of misclassification and fault (in)tolerance? No
5. Additionally, if you are using existing assets (e.g., code, data, models) or curating/releasing new assets, **without compromising anonymity**...
   (a) If your work uses existing assets, did you cite the creators? Yes
   (b) Did you mention the license of the assets? No, I referenced the pre-trained HuggingFace models, along with the website, on which the license is given.
   (c) Did you discuss whether and how consent was obtained from people whose data you're using/curating? NA
   (d) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? No, we include examples of comments in section 5.3 but without the commenters' name and translated so not identifiable.
   (e) If you are curating or releasing new datasets, did you discuss how you intend to make your datasets FAIR (see **?**)? NA
   (f) If you are curating or releasing new datasets, did you create a Datasheet for the Dataset (see **?**)? NA
6. Additionally, if you used crowdsourcing or conducted research with human subjects, **without compromising anonymity**...
   (a) Did you include the full text of instructions given to participants and screenshots? NA
   (b) Did you describe any potential participant risks, with mentions of Institutional Review Board (IRB) approvals? NA
   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? NA
   (d) Did you discuss how data is stored, shared, and deidentified? NA

A Interviewee Extraction Task

Prompt for interviewee extraction from a concatenation of a video's title and description.

```
'''
Instruction:
Extract only the full personal names of
people who are invited in the video.
Exclude titles, roles, affiliations,
and political parties.
Exclude people who are only mentioned
but not invited or speaking. If no
speakers, return an empty list.

  Output format (strict):
"Invited": ["Full Name 1", "Full Name
2"]

  You must output only valid JSON, no
explanations, no text outside the JSON

  Examples:

-Input: Titre: "Interview exclusive avec
Emmanuel Macron et Jean Dupont"
Description : "Le président Emmanuel
Macron s'entretient avec Jean Dupont
sur les enjeux actuels."
-Output:"Invited": ["Emmanuel Macron",
"Jean Dupont"]

-Input: Titre: "Hommage à Simone Veil"
Description: "Le président a évoqué
Simone Veil dans son discours."
-Output:"Invited": []

  Now analyze the following:
'''
```

Models' Performances.

model	precision	recall	f1-score
gpt-4o	**0.94**	0.63	0.75
gpt-4o-mini	0.68	0.88	0.77
flan-t5-base	0.72	**0.89**	0.79
mistral-24B	0.78	0.82	**0.8**

Table 2: Performances of each model on the extraction of interviewee task. Measures with the highest score were put in bold.

B Collection of channels along with their individual upload metrics, engagement metrics and network metrics.

Individual channel upload and engagement metrics are shown in Table 3 for NM channels and in Table 4 for PP channels. Individual channel network measures are shown in Table 5 for NM channels and in Table 6.

Channel	Metrics					
	subs	vids	%S	views	likes	com.
Left						
L'Humanité	183k	208	68.8	64.2k	3.0k	474
Le Média	1.1M	286	0.0	103k	3.6k	737
Mediapart	800k	115	29.6	85.7k	2.3k	315
Blast	1.1M	167	2.4	**238k**	**9.9k**	**1.3k**
Center						
28 minutes	513k	241	0.4	29.2k	506	146
AFP	1.6M	1797	13.4	11.3k	116	51.7
C dans l'air	769k	588	0.0	41.0k	328	81.6
C à vous	929k	1103	6.3	34.6k	333	124
FRANCE 24	**6.7M**	4533	1.4	39.5k	315	113
France Inter	1.2M	2061	1.8	31.8k	657	73.7
LCP	259k	647	4.9	29.5k	289	135
Le Monde	1.8M	170	34.1	124k	2.2k	698
Le Nouvel Obs	400k	300	6.3	28.3k	293	211
LeHuffPost	1.4M	862	4.1	51.8k	635	241
Marianne	148k	65	1.5	43.9k	1.6k	297
Public Sénat	508k	1123	10.3	18.4k	193	109
RFI	1.6M	778	3.2	43.1k	276	56.5
RTL	842k	2375	43.7	41.7k	615	60.4
TV5MONDE Info	1.9M	2864	1.5	23.8k	181	46.7
Euronews	2.1M	2263	0.0	10.4k	91.2	56.5
franceinfo	587k	871	21.6	16.2k	267	127
Libération	55.4k	104	70.2	24.7k	591	63.9
Right						
BFMTV	2.0M	1166	41.0	65.9k	989	469
CNEWS	491k	379	**72.8**	23.5k	592	54.7
Europe 1	1.7M	**5680**	3.5	20.1k	293	111
L'Express	152k	178	66.9	7.3k	98.2	21.3
LCI	1.4M	1006	11.5	131k	1.6k	891
Le Figaro	694k	759	22.1	32.6k	557	175
Le Parisien	1.5M	1384	28.7	159k	3.3k	354
Le Point	292k	1097	1.4	9.9k	61.3	92.7
Les Echos	244k	115	20.9	28.5k	345	69.3
RMC	541k	487	10.5	53.5k	255	354
Sud Radio	974k	3995	2.1	8.3k	267	72.9
TF1 INFO	780k	1063	24.7	130k	2.4k	352
VA Plus	449k	154	66.9	56.6k	2.7k	332

Table 3: **NM channel statistics.** The upload metrics are *vids* for the number of videos and *%S* for the percentage of videos that are Shorts. The engagement metrics are *subs* for the number of subscribers at the moment of collection, and *views*, *likes*, and *coms* for the average number of views, likes and comments on videos from the corresponding channels at the moment of collection.

Channel	Metrics					
	subs	vids	%S	views	likes	com.
Far Left						
LO	3.2k	39	0.0	946	41.1	15.0
NPA	29.1k	77	2.6	12.0k	725	171
Left						
PCF	47.4k	**304**	49.3	50.5k	1.8k	218
LFI	117k	99	8.1	22.1k	1.4k	238
F. Ruffin (EcoS)	258k	60	68.3	87.4k	4.5k	460
JL. Mélenchon (LFI)	**1.1M**	140	50.7	307k	13.7k	1.2k
M. Aubry (LFI)	26.9k	120	9.2	22.8k	1.3k	495
M. Bompard (LFI)	89.4k	84	29.8	157k	7.6k	1.1k
M. Panot (LFI)	237k	78	24.4	123k	6.5k	1k
R. Hassan (LFI)	26.1k	20	75.0	279k	12.9k	1.4k
EELV	7.2k	98	1.0	7.3k	230	106
PS	13.3k	82	13.4	3.0k	64.8	53.0
PP-Place Publique	2.3k	193	12.4	781	12.9	13.4
Center						
G. Attal (RE)	2.9k	4	25.0	52.0k	501	320
E. Macron (RE)	339k	29	41.4	47.4k	1.4k	651
MoDem	8.9k	84	0.0	1.5k	12.3	12.8
UDI	483	23	0.0	254	3.61	0.48
Right						
UPR	455k	54	1.9	97.1k	6.5k	887
F. Asselineau (UPR)	53.1k	82	26.8	124k	5.6k	477
LR	24.3k	12	0.0	1.7k	58.5	25.2
N. Dupont-Aignan (DLF)	165k	105	65.7	36.9k	4.9k	531
Far Right						
RN	49.3k	143	**98.6**	52.4k	3.0k	217
M. Le Pen (RN)	107k	126	81.0	206k	8.6k	774
J. Bardella (RN)	96.1k	159	61.6	**312k**	12.6k	1.2k
LP	25.8k	6	0.0	14.3k	2.4k	466
F. Philippot (LP)	511k	155	2.6	134k	**16.4k**	1.8k
E. Zemmour (REC)	480k	42	28.6	160k	6.1k	**1.9k**
M. Maréchal (REC-RN)	95.0k	100	32.0	89.9k	4.0k	1.1k

Table 4: **PP channel statistics.** The upload metrics are *vids* for the number of videos and *%S* for the percentage of videos that are Shorts. The engagement metrics are *subs* for the number of subscribers at the moment of collection, and *views*, *likes*, and *coms* for the average number of views, likes and comments on videos from the corresponding channels at the moment of collection.

Channel	VCG		AVCG			CPWG
	comp.	dens.	dens.	trans.	diam.	dens.
Left						
L'Humanité	1	1.3e-04	**4.2e-03**	0.36	8	0.061
Le Média	1	9.9e-05	2.6e-03	0.24	6	0.040
Mediapart	1	2.5e-04	8.4e-04	0.17	6	0.065
Blast	1	6.5e-05	2.5e-03	0.22	6	0.046
Center						
28 minutes	3	1.9e-04	4.8e-04	0.14	9	0.031
AFP	116	9.6e-05	2.3e-04	0.09	14	0.009
C dans l'air	3	5.8e-04	6.9e-04	0.02	12	0.059
C à vous	19	7.5e-05	4.8e-04	0.18	11	0.022
FRANCE 24	52	3.8e-05	2.8e-04	0.13	12	0.007
France Inter	51	7.9e-05	8.0e-04	0.27	10	0.023
LCP	19	9.4e-05	7.7e-04	**0.46**	10	0.039
Le Monde	1	6.9e-05	7.5e-04	0.21	6	0.041
Le Nouvel Obs	13	1.1e-04	3.8e-04	0.14	10	0.029
LeHuffPost	3	6.9e-05	5.9e-04	0.15	8	0.018
Marianne	1	2.9e-04	2.1e-03	0.28	6	**0.115**
Public Sénat	8	8.5e-05	3.6e-04	0.13	10	0.019
RFI	75	1.1e-04	2.2e-04	0.12	12	0.013
RTL	73	9.0e-05	4.1e-04	0.16	12	0.016
TV5MONDE Info	**169**	7.2e-05	2.2e-04	0.12	12	0.008
Euronews	35	1.5e-04	7.1e-04	0.14	11	0.014
franceinfo	11	8.6e-05	3.9e-04	0.15	8	0.019
Libération	8	5.1e-04	7.3e-04	0.10	13	0.064
Right						
BFMTV	4	2.9e-05	1.3e-03	0.30	10	0.037
CNEWS	19	2.6e-04	5.7e-04	0.21	10	0.046
Europe 1	94	4.8e-05	9.9e-04	0.19	12	0.016
L'Express	35	**8.9e-04**	9.8e-04	0.01	**18**	0.050
LCI	2	6.6e-05	3.0e-03	0.28	6	0.027
Le Figaro	3	9.4e-05	4.3e-04	0.19	10	0.030
Le Parisien	4	3.7e-05	4.4e-04	0.13	8	0.014
Le Point	39	1.4e-04	7.5e-04	0.16	11	0.018
Les Echos	12	4.9e-04	5.3e-04	0.01	10	0.042
RMC	1	6.9e-05	1.0e-03	0.25	7	0.036
Sud Radio	63	9.1e-05	1.4e-03	0.21	9	0.025
TF1 INFO	3	3.9e-05	5.4e-04	0.17	9	0.018
VA Plus	1	2.2e-04	1.4e-03	0.17	6	0.036

Table 5: **NM channel network measures.** Number of components (*comp.*) and density (*dens.*) for the VCG; density (*dens.*), transitivity (*trans.*), and diameter (*diam.*) for the AVCG; and density (*dens.*) for the CPWG, reported for each NM channel.

Channel	VCG		AVCG			CPWG
	comp.	dens.	dens.	trans.	diam.	dens.
Far Left						
LO	1	1.2e-02	1.5e-02	0.17	6	0.161
NPA	1	5.5e-04	5.0e-03	0.38	6	0.103
Left						
PCF	1	1.5e-04	1.4e-03	0.31	8	0.056
LFI	1	4.4e-04	3.1e-03	0.39	6	0.080
F. Ruffin (EcoS)	1	2.5e-04	2.4e-03	0.29	6	0.076
JL. Mélenchon (LFI)	1	8.1e-05	3.2e-03	0.27	6	0.048
M. Aubry (LFI)	1	3.4e-04	7.7e-03	0.32	6	0.091
M. Bompard (LFI)	1	1.4e-04	6.9e-03	0.32	6	0.085
M. Panot (LFI)	1	1.1e-04	3.3e-03	0.37	6	0.137
R. Hassan (LFI)	1	2.4e-04	5.4e-03	**0.54**	4	0.256
EELV	3	5.9e-04	4.3e-03	0.35	8	0.149
PS	4	1.3e-03	2.3e-03	0.11	8	0.141
PP (Place Publique)	**14**	1.5e-03	1.7e-03	0.06	**12**	0.027
Center						
G. Attal (RE)	1	3.5e-03	3.7e-03	0.00	4	0.408
E. Macron (RE)	1	4.0e-04	3.1e-03	0.31	4	0.150
MoDem	9	2.9e-03	3.4e-03	0.03	10	0.105
UDI	3	**1.4e-01**	**3.3e-01**	0	2	**1**
Right						
UPR	1	2.5e-04	9.3e-03	0.34	6	0.151
F. Asselineau (UPR)	1	2.1e-04	3.3e-03	0.38	6	0.084
LR	2	1.2e-02	1.3e-02	0.03	8	0.192
N. Dupont-Aignan (DLF)	1	2.5e-04	7.2e-03	0.33	6	0.096
Far Right						
RN	1	4.0e-04	3.5e-03	0.24	6	0.063
M. Le Pen (RN)	1	1.6e-04	4.7e-03	0.27	6	0.084
J. Bardella (RN)	1	9.1e-05	4.0e-03	0.25	6	0.054
LP	1	2.3e-03	1.3e-02	0.49	4	0.359
F. Philippot (LP)	1	1.8e-04	1.8e-02	0.34	4	0.097
E. Zemmour (REC)	1	1.9e-04	9.3e-03	0.35	6	0.110
M. Maréchal (REC-RN)	1	1.8e-04	7.7e-03	0.32	4	0.083

Table 6: **PP channel network measures.** Number of components (*comp.*) and density (*dens.*) for the VCG; density (*dens.*), transitivity (*trans.*), and diameter (*diam.*) for the AVCG; and density (*dens.*) for the CPWG, reported for each PP channel.