Social Media Data Analysis - Final Project: Cross-Partisan Discussions on German YouTube

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1 Motivation and Background

Filter bubbles and echo chambers are central concepts in the analysis of online discourse, though often used interchangeably, they denote distinct mechanisms. Filter bubbles refer to algorithmic personalization, where users are predominantly exposed to content aligned with their preferences. Echo chambers, by contrast, reflect the social effects of this personalization, driven by human tendencies toward cognitive consonance and group reinforcement. These environments may entrench existing beliefs and exclude opposing views, potentially undermining dialogue, deepening polarization, and, in extreme cases, threatening democratic norms (de Luca, 2024). Some claim that such dynamics are not unique to the digital age. However, social media platforms offer new structural affordances that amplify their reach (Stegman, as quoted in de Luca (2024)). Other scholars challenge the extent or very existence of digital echo chambers, pointing to the diversity of online content, the continued influence of traditional media, and the disproportionate visibility of vocal minorities compared to a largely moderate majority (Borchardt, 2020).

A key empirical contribution to this debate is the study by Wu and Resnick (2021), which examines cross-cutting political communication on YouTube. Analyzing 274,000 videos from 973 channels and 134 million comments from over nine million users, they assess the prevalence of "cross-talk", or user's commenting activity across ideological lines. Media outlets were classified as left or right using Media Bias/Fact Check (MBFC), and user leanings inferred using a hierarchical attention network. The findings reveal asymmetric cross-partisan interaction: while users from both sides engage across divides, right-leaning users are more likely to comment on left-leaning content than the reverse—particularly within independent media. A similar asymmetry is observed at the user level, where conservative users are significantly more likely to venture and comment on left-leaning videos than vice versa.

Their results align with earlier work by Heatherly et al. (2017), who found that online networks support both like-minded and cross-cutting interactions. Mainstream platforms tend to amplify moderate voices while sidelining extremist ones, and rarely foster interaction among the most polarized users.

Wu and Resnick (2021) also provide the foundation for Chae and Lee (2024), who analyze user interactions on YouTube across vlogger and mainstream news content. Despite a smaller sample, they replicate the observed asymmetry: conservative users engage more frequently with liberal content than vice versa, particularly in vlogger comment sections. Their study also highlights the potential of politically neutral news channels to promote more balanced cross-partisan discourse.

While extensive research examines these dynamics in the U.S. context, evidence from Germany remains limited and often focuses on intra-partisan communication (e.g., (Rauchfleisch & Kaiser, 2020)). Addressing this gap, the present study replicates the methodological framework of Wu and Resnick (2021) to conceptualize and measure cross-cutting political communication on German YouTube. Based on this framework, three hypotheses are derived:

H_1: Right users are more likely to comment on left-leaning channels than left users on right-leaning.

H_2: Left-leaning videos exhibit a higher share of right comments in their comment sections than right-leaning videos of left comments.

H_3: Independent media channels exhibit less cross-talk than mainstream media.

2 Data Collection

Similar to the replicated study, Media Bias/Fact Check serves as the starting point for data collection, given the absence of a comprehensive classification of German media outlets. Filtered to German sources, "Media Bias/Fact Check" (2024) provides a five-point ideological scale for 74 outlets, ranging from "right" to "left", alongside categories such as "pro-science", "questionable sources", "conspiracy-pseudoscience", and "satire". These labels were scraped and matched to YouTube channels using outlet names and the *ChannelsSearch* function from the *googleapiclient* Python library. Ten channels were manually corrected after review; eleven were excluded due to missing matches. In contrast to Wu and Resnick (2021), all channels along the five-point scale are retained to reflect ideological variation in the German media landscape. "Pro-science" is merged with "least biased" under "news/science," and "questionable" or "conspiracy" sources are recoded as "right." The satire channel Postillon is excluded.

The sample is supplemented with 11 left-leaning channels (from Liedtke and Marwecki (2019)), 14 right-leaning channels (from Frank (2019), Haque et al. (2024), and Sick et al. (2024)), and an additional labeled set compiled by a former master's student. Official party channels are recoded: CDU as "right center," SPD and the Greens as "left center". This results in a starting set of 106 Stage-1 channels (Figure 1).

Similar to Wu and Resnick (2021), featured channels were scraped from Stage-1 YouTube pages and assigned the parent channel's leaning, yielding 120 additional Stage-2 channels.

Before video and comment retrieval, the full channel set was filtered. Only German or language-unknown channels with at least one upload were retained. Channels targeting non-German audiences or focused narrowly on topics like sports, cars, or fictional entertainment were excluded, as were academic institutions with low engagement. In contrast, pop-cultural news, satire, and comedy were explicitly retained. Inactive, secondary accounts by left-leaning influencer "Rezo" were also removed. Channels of regional party offices were excluded to prevent overrepresentation. Additional channels were added to represent all Bundestag parties, youth wings, regional public broadcasters, and some remaining prominent media outlets such as Welt, Stern, and Simplicissimus. The final sample comprises 30 left, 39 left-center, 42 news/science, 24 right-center, and 34 right channels. Following the Wu and Resnick (2021)'s classification, channels were also categorized as "National Media" (40), "Local Media" (28), "Organizations" (28), and "Independent Media" (69).

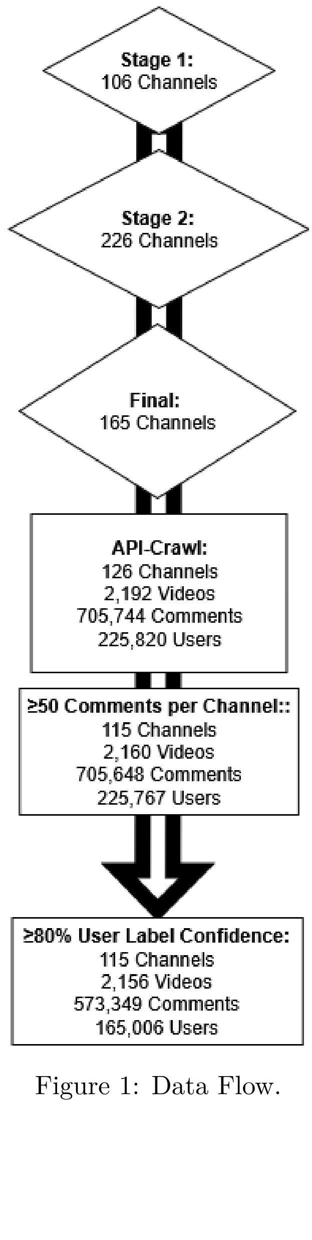


Figure 1: Data Flow.

Unlike the original study, this project does not aim for exhaustive data coverage. API constraints, time, and computational limits required a focus on relevance within a defined time window. This strategy is supported by Munger et al. (2025), who show that attention on YouTube is highly unequal, with the majority of engagement concentrated on a small subset of channels and users. Similarly, the replicated authors report only small biases when limiting analysis to the top 20 comments per video, with broader engagement patterns unaffected.

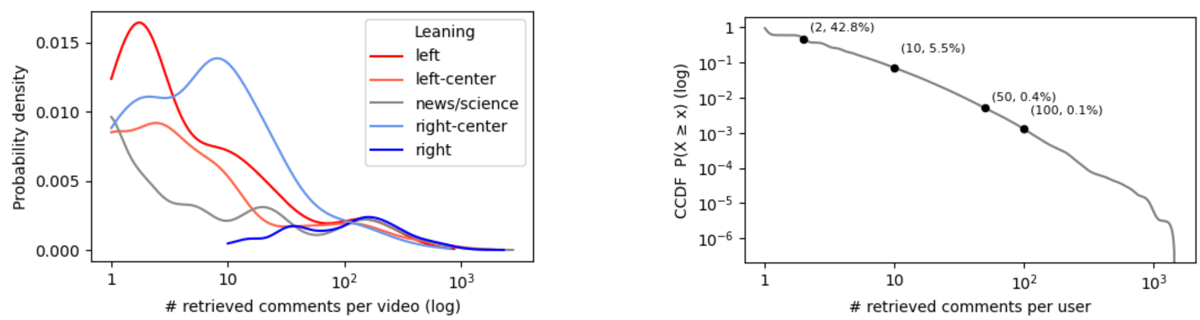
Upload playlists were retrieved via the YouTube API (*channels* and *playlistItems* endpoints) to identify up to 100 candidate videos per channel, posted between 06/24/2024 and 08/08/2024.[1] From these, the top 20 videos by comment count were selected. For each video, up to 100 top-level comments (by relevance) and up to 100 replies per comment were retrieved.[2] No data could be retrieved for 39 channels, and nine more were excluded for having fewer than 50 total comments.

Unlike the original study, no topic-based filtering of videos was applied. Of the 2,160 videos retrieved, only 129 were categorized outside of politics, society, entertainment, or related fields. While some were labeled with peripheral topics (e.g., music, health), they often originated from political channels or addressed socially relevant issues. Others lacked a topic label altogether. All videos were retained to preserve breadth.

Table 1 summarizes the collected data: 705,648 comments from 225,820 users. News/science channels yielded the most content, while left and right channels are represented in nearly equal numbers. Within the left category, most content stems from left-center channels; within the right, strictly right-leaning channels dominate. Although more videos and comments were collected from right-leaning channels, left-center channels generated more total views. Right channels also show high commenting activity but lower retrieval rates, suggesting that while top-level engagement may be strong, left-center and news/science videos generate more reply-based discussion.

	left	left-center	news/science	right-center	right	total
#channels retrieved	18	23	34	11	29	115
#videos retrieved	316	439	663	187	555	2160
#views	4.94×10^7	2.04×10^8	2.24×10^8	1.70×10^7	8.33×10^7	5.78×10^8
#comments	220,931	642,432	748,841	59,532	894,094	2,565,830
#comments retrieved	63,472	171,651	241,536	29,157	199,832	705,648
comment retrieval rate (%)	28.7	26.7	32.3	49.0	22.4	27.5

Table 1: Statistics of YouTube crawl. Filtered to channels with ≥ 50 retrieved comments.



(a) PDF: Retrieved comments per video by leaning.

(b) Log CCDF: Retrieved comments per user.

Figure 2: Probability distributions of retrieved comments.

Figure 2a shows the distribution of comment volume (log-transformed), indicating that strictly right

[1]This window balances recency with a 45-day buffer before the reference date (08/08/2025), following Wu and Resnick (2021), citing Wu et al. (2018)'s evidence that over 90% of views occur within the first 45 days.

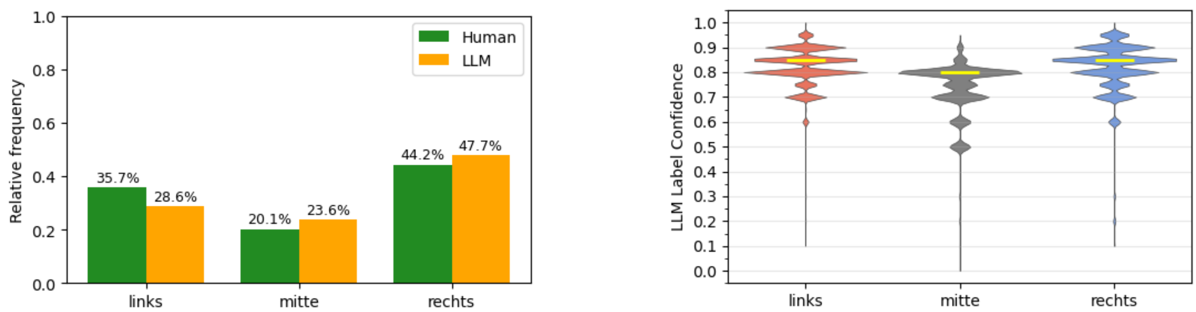
[2]Comment collection took place between 08/08/2025 and 08/19/2025.

channels have a higher proportion of high-engagement videos, while left and right-center videos exhibit lower volumes more frequently. Figure 2b presents the complementary cumulative distribution function (CCDF) of user comment counts. While Wu and Resnick (2021) retained only active users with ≥10 comments (16.7% of users), applying this threshold here would capture only 5.5%. Even a two-comment threshold would exclude over half the user base. Therefore, no such restriction is applied.

3 Predicting User Political Leaning with LLM

To infer user political leaning, Wu and Resnick (2021) employ a hierarchical attention network (HAN) trained on comments from 162,000 pre-labeled seed users. The model predicts conservativeness based on a user's concatenated comments and classifies users as "conservative" (≥ 0.95), "liberal" (≤ 0.05), or "unknown" (excluded). It achieves an accuracy of 0.929. Applying the HAN here is infeasible for two reasons: the limited number of users and comments renders the creation of a sufficiently large seed set impractical, and the binary classification omits moderate users, which may be analytically interesting given the more granular categorization of German channels.

Instead, this study uses a local large language model, *Qwen2.5:14b-instruct-q4_K_M*, deployed via *Ollama*, to assign three-way user labels: "links" (left), "mitte" (center), and "rechts" (right). Though not explicitly trained on political data, Qwen 2.5 demonstrates strong performance in political content classification (Martinez-Serra et al., 2025) and achieves high benchmark scores (Ahmed et al., 2025; Fan, 2024). Its multilingual architecture ensures robust German-language support, and its 14-billion parameter capacity offers a balance of efficiency, memory usage, and extended context handling (up to 131,072 tokens) (Qwen, 2025).



(a) Human vs. LLM user annotations.

(b) LLM labeling confidence with medians.

Figure 3: LLM User labeling.

For each user, up to twelve of their most recent comments are processed alongside contextual metadata, specifically video title, description, root or parent comment, and @mentions. No information about the video's channel or political leaning is included to avoid label leakage. Prompts are constructed in German within a 4,096-token context window, using truncated character limits (comments: 320, titles: 140, descriptions: 220). The model is prompted to return strictly formatted JSON: { "label": "links|mitte|rechts", "confidence": 0..1 }. If formatting fails, a soft fallback attempts to correct the output; persistent errors trigger a hard fallback assigning "mitte" with zero confidence.

This method was benchmarked against manual annotations for 200 randomly sampled users and mirrors the structure of human coding (see Figure 3a). Figure 3b shows the distribution of LLM-assigned confidence scores in intervals of 0.05. To increase reliability, the final user sample is filtered using a median confidence threshold of 0.8 for the "mitte" category. This yields 80,526 users labeled as "rechts," 56,565 as "links," and 27,915 as "mitte."

4 Prevalence Analysis

Since the analysis is not limited to active users, a substantial proportion of users within each group have never commented on most leanings. As a result, reporting median comment shares, as done by Wu and Resnick (2021) for active users, is not meaningful in this context. Instead, the analysis relies on average comment shares within groups for both user- and video-level perspectives. Each estimate is based on 5,000 bootstrap samples drawn with replacement at group size, with corresponding bootstrap errors and 95%-confidence intervals reported.

4.1 H_1: Right users are more likely to engage in cross-commenting than left users

User \ Channel	left	left-center	news/science	right-center	right
links	20.9	38.6	40.0	4.4	21.2
mitte	9.7	31.3	59.3	6.5	5.8
rechts	10.3	28.3	33.6	7.2	52.6

Table 2: Per group share of users which commented on channel leaning at least once.

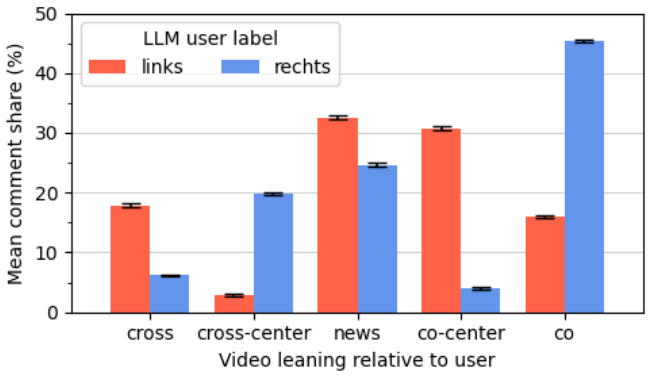
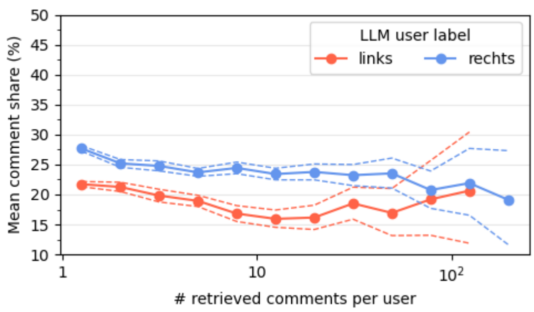
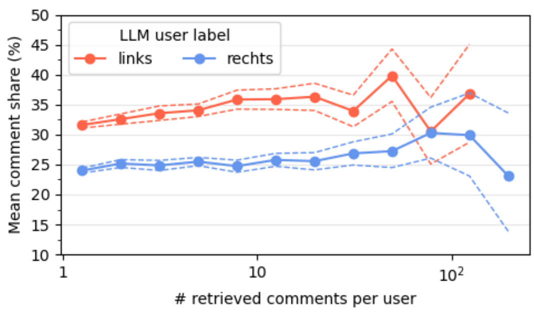


Figure 4: Mean share of comments of users on opposite, opposite-center, news/science, own-center, and own leaning. Error bars display bootstrap 95%-confidence.



(a) Mean share of comments on opposite leaning.



(b) Mean share of comments on news/science.

Figure 5: Mean cross-cutting comment share of user by number of comments. 15 equal width-bins, minimum bin size for display is 20 users. Dashed lines display upper and lower bounds of bootstrap 95%-confidence.

Both left- and right-labeled users engage with content from channels of opposing political leanings. Figure 5a, which collapses "opposite" and "opposite-center" into a single category, shows that right users consistently exhibit a higher average share of cross-cutting comments compared to left users. Figure 4 further indicates that this tendency among right users is largely directed at left-center content. In contrast, when left users engage in cross-cutting commenting, it is more frequently directed at strictly right channels. However, as Figure 4 also illustrates, the alternative hypothesis—that left users are equally or even more likely to engage in cross-cutting behavior—cannot be fully dismissed when comments on "neutral ground" are included (see also Figure 5b and Table 2). While right users are most likely to comment within their own ideological sphere, particularly on strictly right channels, left users show a more dispersed commenting pattern, with a notable focus on news and left-center content. Thus, although right users are more likely, on average, to engage with opposing content—especially left-center channels—left users exhibit a broader commenting distribution oriented more toward centrist channels.

4.2 H_2: Left-leaning videos exhibit a higher share of cross-cutting comments than right-leaning videos

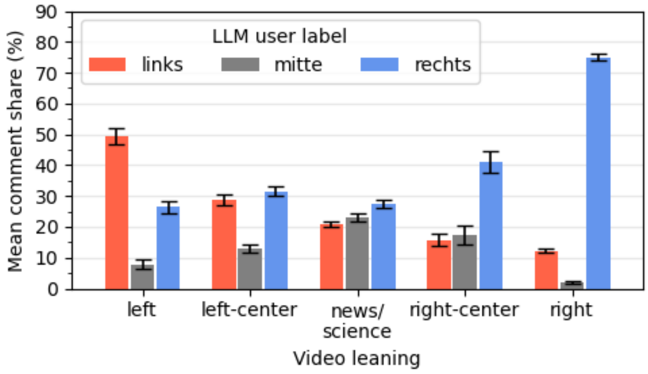
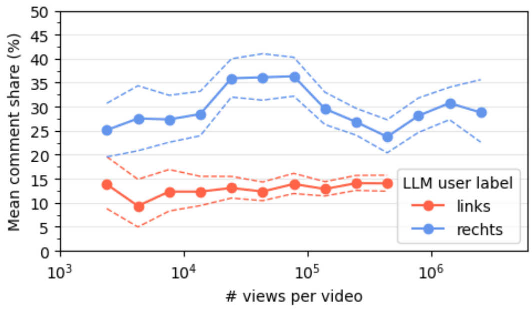
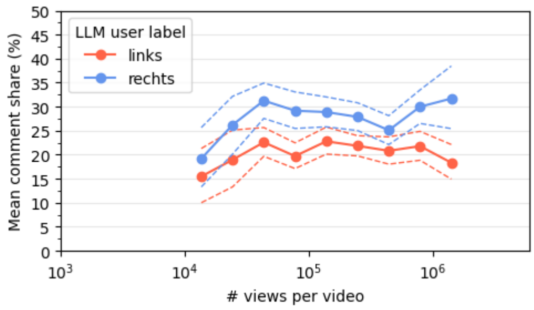


Figure 6: Mean comment composition of videos. Error bars display bootstrap 95%-confidence.



(a) Mean share of comments from opposite leaning.



(b) Mean share of comments on news/science.

Figure 7: Mean share of cross-cutting comments under videos ($\geq$ 1,000 views). 15 equal width-bins, minimum bin size for display is 20 videos. Dashed lines display upper and lower bounds of bootstrap 95%-confidence.

Videos from left-leaning channels show a strong average presence of comments from right-labeled users, while comment sections of right-leaning channels also remain dominated by right users, with comparatively low participation from the left (see Figure 7a). Notably, right user comments are also prevalent under left-center and news videos, despite previously identified high engagement from left users in those spaces. These patterns support the rejection of the alternate hypothesis that left-leaning videos do not attract a higher share of cross-cutting comments than right-leaning ones. However, Figures 6 and 7b also indicate that the representational gap between left, right, and centrist users is narrowest under news and left-center content, suggesting that such videos may serve as key venues for cross-cutting discussion.

4.3 H_3: Independent media exhibits less cross-talk than mainstream media

Cross-talk is defined as the proportion of comments from ideologically opposing users relative to the total number of left and right comments on a channel's videos. For left- and right-leaning channels, it reflects the share of comments from users of the opposite leaning. For news channels, it is calculated as one minus the absolute difference between left and right comments divided by their sum, with higher values indicating greater ideological mixing. Figure 8 displays bootstrapped mean estimates of cross-talk across channel types. National and local mainstream media show high average levels, driven by balanced comment sections on news channels and a notable share of right-leaning comments on left-center outlets. In contrast, independent media and organizations exhibit significantly lower cross-talk, largely due to strictly right-leaning independent channels: Nine of the ten lowest cross-talk scores fall into this category, with the tenth from a right-leaning organization. These findings prompt rejection of the alternative hypothesis that independent media does not exhibit lower cross-talk than mainstream media.

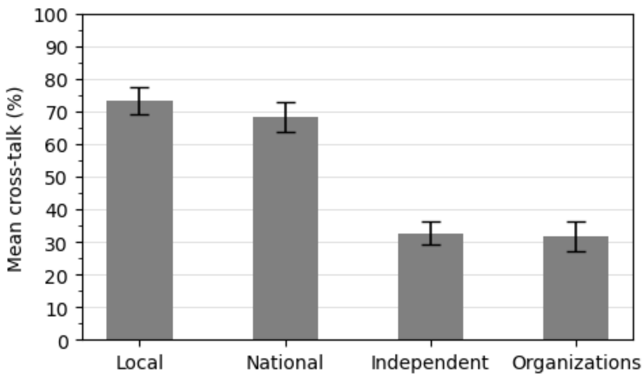


Figure 8: Mean cross talk by channel category. Error bars display bootstrap 95%-confidence.

5 Discussion

Above results broadly align with Wu and Resnick (2021)'s evidence of asymmetric cross-talk. On average, both partisan groups direct more than half of their commenting activity toward content outside their ideological camps, with right-leaning users contributing disproportionately to left-leaning channels. Moreover, left-leaning channels receive higher average levels of cross-talk than their right-leaning counterparts. Cross-talk is also more prominent on mainstream national and local media channels, while independent media and organizations show notably lower levels.

The analysis further reveals important distinctions in user engagement patterns. Left-leaning users lack a clearly aligned content base and instead concentrate their activity on moderate outlets, including news/science and left-center channels. In contrast, right-leaning users are more likely to engage with ideologically aligned content, occasionally crossing over to the left. In this context, the idea that cross-cutting engagement prevents echo-chamber formation remains inconclusive. A more nuanced understanding of echo chambers, cross-talk, and their interrelationship is needed. While Wu and Resnick (2021) offer insights into the toxicity of cross-partisan interactions, they also emphasize the need for qualitative research into the motivations behind engagement both within and beyond users' ideological orientations.

Another notable finding concerns the role of left-center and news/science channels in facilitating balanced discussion. These outlets attract a more ideologically diverse audience and show elevated levels of cross-partisan engagement. Their comment sections often feature a mix of political perspectives, suggesting that such content may support exposure to divergent views and foster deliberative exchange. These characteristics underscore the potential of such platforms to mitigate ideological segregation. Future research should examine the specific content and moderation practices that enable such engagement, with implications for platform design and policy aimed at reducing polarization.

Despite its ideological granularity, the scope of this analysis is limited in both breadth and depth, affecting detail and generalizability of its findings. The selection of channels, videos, and comments, along with the resulting user base, captures only a narrow segment of the overall platform. Reliance on a small subset of available data constrains labeling performance and necessitates the use of group-level mean aggregates, a method vulnerable to distortion by highly active minorities. Unlike Wu and Resnick (2021), who apply a median-based analysis for finer resolution, this study accepts reduced detail at the user and video levels.

Moreover, all findings rest on the assumed relevance of the retrieved content, and thus reflect only a visible and active portion of the German YouTube landscape. It remains possible that the prominence of right-leaning engagement is driven by its visibility in highly active or controversial videos, while left-leaning users may be more engaged in less prominent or throughout less contentious spaces.

Future research should aim to expand the set of analyzed videos and comments. The current thresholds of 20 videos per channel and 100 top-level comments per video are modest and can be extended with greater investments in API quota and LLM processing time. Enlarging the set of relevant channels poses a greater challenge, as no comprehensive and up-to-date classification of labeled German media outlets exists, let alone one for YouTube. A substantial share of the initial Stage-2 channels, particularly from the strict left and right-center, was excluded due to limited topical relevance or low engagement. A systematic and comprehensive classification of labeled channels would benefit future research and enhance the validity of longitudinal and cross-platform analyses. A more detailed mapping of the German YouTube landscape, as initiated here, requires a broader and more representative foundation of politically and socially relevant content.

A further limitation lies in the unsupervised user labeling via the LLM. Unlike Wu and Resnick (2021), who used a large seed set to fine-tune their model within a specific political context, the LLM applied here lacks task-specific adaptation to German politics or the YouTube domain. Fine-tuning with contextual training data could improve labeling accuracy. The seed user strategy employed by the replicated authors offers a promising template for such efforts.

Model evaluation is likewise constrained. Human and model-generated annotations were compared, and confidence scores elicited, to ensure a minimum validation standard. A key design trade-off involved whether to label comments individually and aggregate at the user level to improve confidence estimates, or to input all available comments per user to maximize contextual understanding. This study opted for the latter. Future work could assess whether comment-level annotation followed by aggregation yields more reliable user classifications. Researchers may also consider validating the model on external pre-labeled datasets or expanding the pool of human annotators to improve evaluation quality and establish more robust benchmarks.

Taken together, these findings contribute to a growing body of research on online political engagement by offering a case-specific yet methodologically adaptable framework for analyzing cross-partisan dynamics on YouTube. While the study is exploratory in nature, it underscores the importance of platform-specific affordances, audience composition, and content type in shaping political discourse. Future research should integrate computational and qualitative methods to capture both structural patterns and user motivations. As political communication continues its migration to digital platforms, understanding the mechanisms that foster or hinder deliberative engagement will be central to mitigating polarization in online environments.

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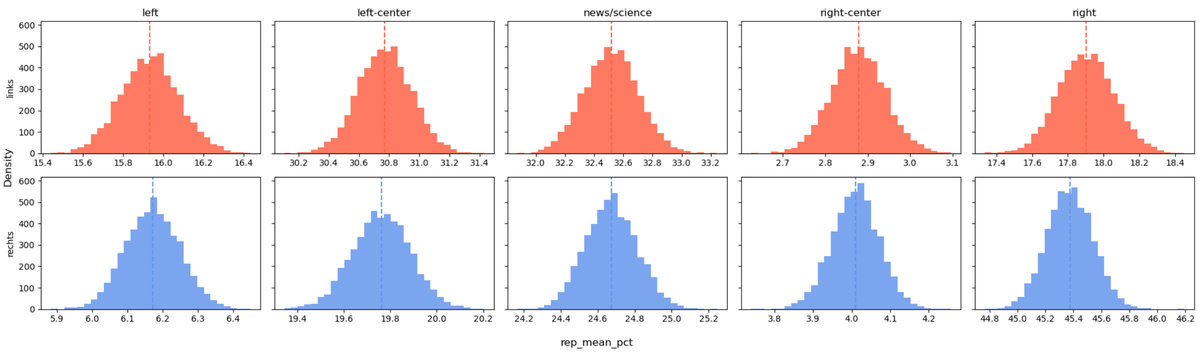
Appendix

Code for data collection, LLM labeling, and analysis as well as visualizations and the crawled dataset with labeled users is confidentially available at a private GitHub repository. The examiner has been granted access.

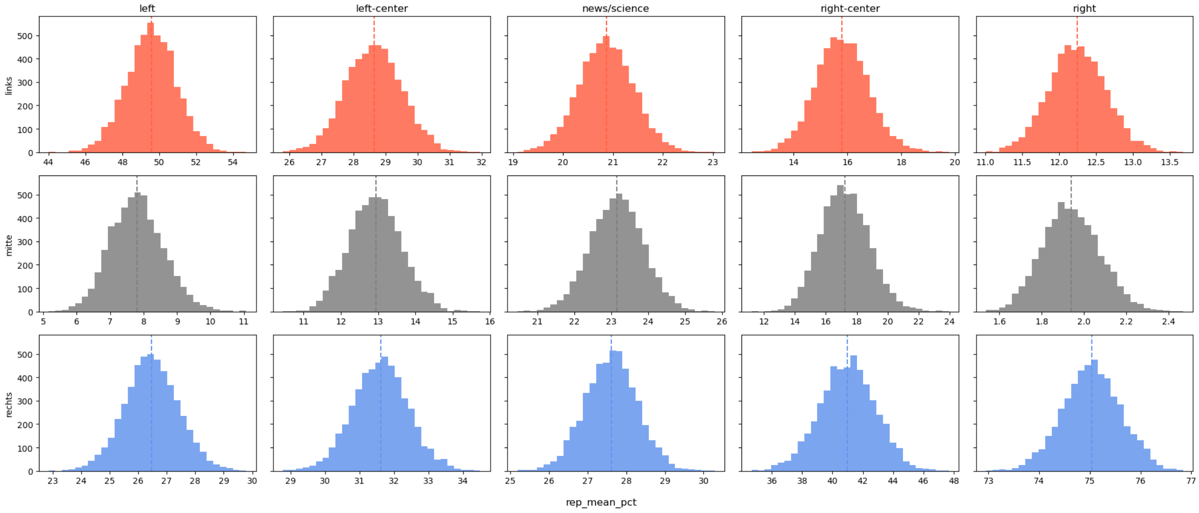
LLM Prompt Example

```
<|system|>
You are a concise political stance classifier for German text. Return ONLY a single JSON object with keys 'label' and 'confidence'. No prose. No markdown. No additional fields. No explanations.
<|user|>
Klassifiziere die politische Ausrichtung dieses Nutzers als genau EINES von:
"links", "mitte" oder "rechts".

Regeln:
- Berücksichtige den Kontext (Kanal/Video), aber entscheide nach dem Gesamtbild über alle Kommentare.
- Antworte NUR als JSON: { "label": "links|mitte|rechts", "confidence": 0..1 }
- Keine Erklärungen, kein Fließtext, keine zusätzlichen Felder.

Kommentare (gebündelt):
  1) Video-Titel: Verfassungsschutz: Ganze AfD „gesichert rechtsextrem“ – Blitz-Analyse mit Prof. Boehme-Neßler
  Video-Beschreibung: Die ganze AfD wird jetzt vom Verfassungsschutz als „gesichert rechtsextrem“ eingestuft: Nancy Faeser schließt ein Verbotsverfahren nicht mehr aus. Der Verfassungsrechtler Prof. Volker Boehme-Neßler analysiert bei Apollo…
  Antwort auf: »Was für ein durchschaubares Theater. WEN will Frau Faeser mit sowas überzeugen?«
  Kommentar von User: *Wir werden die schmutzig braune AfD rauswerfen. Keine Macht den Nazis.*

  2) Video-Titel: Verfassungsschutz: Ganze AfD „gesichert rechtsextrem“ – Blitz-Analyse mit Prof. Boehme-Neßler
  Video-Beschreibung: Die ganze AfD wird jetzt vom Verfassungsschutz als „gesichert rechtsextrem“ eingestuft: Nancy Faeser schließt ein Verbotsverfahren nicht mehr aus. Der Verfassungsrechtler Prof. Volker Boehme-Neßler analysiert bei Apollo…
  Antwort auf: »Die Frau ist sich aber auch für nichts zu schade.«
  Kommentar von User: *Wir werden die schmutzig braune AfD rauswerfen. Keine Macht den Nazis.*

  3) Video-Titel: Verfassungsschutz: Ganze AfD „gesichert rechtsextrem“ – Blitz-Analyse mit Prof. Boehme-Neßler
  Video-Beschreibung: Die ganze AfD wird jetzt vom Verfassungsschutz als „gesichert rechtsextrem“ eingestuft: Nancy Faeser schließt ein Verbotsverfahren nicht mehr aus. Der Verfassungsrechtler Prof. Volker Boehme-Neßler analysiert bei Apollo…
  Antwort auf: »Stasi Manieren. Langsam komme ich als 91-jähriger zum Schluß, die DDR ist fast gleich der BRD«
  Kommentar von User: *Wir werden die schmutzig braune AfD rauswerfen. Keine Macht den Nazis.*
```

User Bootstrap Distribution



Video Bootstrap Distribution



Channel Bootstrap Distribution