Solovev et al. *EPJ Data Science* (2026) 15:29
https://doi.org/10.1140/epjds/s13688-026-00632-7

EPJ.org

EPJ Data Science

RESEARCH

Open Access

Engagement with political videos on TikTok during the 2025 German federal election

Kirill Solovev[1], Chiara Drolsbach[1], Emma Demirel[1] and Nicolas Pröllochs[1*]

Handling Editor: Giancarlo RUFFO

*Correspondence:
nicolas.proellochs@wi.jlug.de
[1]JLU Giessen, Giessen, Germany

Abstract

Short-form video platforms like TikTok reshape how politicians communicate and have become important tools for electoral campaigning. Yet it remains unclear what kinds of political messages gain traction in these fast-paced, algorithmically curated environments, which are particularly popular among younger audiences. In this study, we use computational content analysis to analyze a comprehensive dataset of $N = 25{,}292$ TikTok videos posted by German politicians in the run-up to the 2025 German federal election. Our empirical analysis shows that videos expressing negative emotions (e.g., anger, disgust) and outgroup animosity were significantly more likely to generate engagement than those emphasizing positive emotion, relatability, or identity. Furthermore, ideologically extreme parties (on both sides of the political spectrum) were both more likely to post this type of content and more successful in generating engagement than centrist parties. Taken together, these findings suggest that divisive political communication tends to receive higher engagement than unifying messages on TikTok, thereby potentially benefiting extreme actors who are more inclined to capitalize on this logic.

Keywords: Social media; Political communication; Computational content analysis; Online emotions; User engagement

1 Introduction

Short-form video platforms like TikTok have rapidly become central to electoral campaigning, particularly among younger audiences who consume political information in new formats [1, 2]. Unlike traditionally text-focused platforms such as X/Twitter or Facebook, TikTok emphasizes visual storytelling, short-form video, and trend-based interaction [3]. Its algorithmically curated, highly personalized content feed allows political messages to circulate well beyond a politician's follower base, increasing the likelihood of visibility and engagement [4–6]. For example, in Germany, TikTok counts almost 20.9 million users as of 2024 (~35% of all adults [7]), with a particularly high uptake among younger demographics (~55% of users are under the age of 30 [8]). This makes TikTok a crucial channel for reaching first-time voters and politically less-engaged audiences who are less likely to consume traditional news media [1, 2, 9].

© The Author(s) 2026. **Open Access** This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit http://creativecommons.org/licenses/by/4.0/.

Springer

As platforms like TikTok gain political relevance, online political communication has become highly strategic. Politicians have strong incentives to actively craft content that shapes public narratives, mobilizes support, and maximizes engagement in a highly competitive attention economy [10, 11]. To achieve this, politicians can draw on a wide repertoire of rhetorical tools [12–15]. Examples include variation in sentiment (e.g., optimistic vs. pessimistic messages), the use of discrete emotions (e.g., fear to signal threat), and different forms of group-oriented messaging, which can either foster belonging through identity-based appeals [16, 17], or heighten division by targeting outgroups [18, 19]. Such strategies may help politicians to resonate with specific voter segments, reinforce in-group loyalty, and signal alignment on salient issues [20, 21]. Yet, despite the variety of available strategies, it remains largely unclear which types of political content are actually rewarded by users and platform algorithms on short-form video platforms like TikTok.

Prior research on online political communication has largely focused on primarily text-based social media platforms (e.g., X/Twitter, Facebook) and the political context of the U. S. For instance, affective content – particularly negative sentiment and emotions such as anger – has been shown to be associated with higher user engagement (e.g., shares, likes) [9, 19, 22–24]. Similarly, the use of outgroup language (i.e., expressing hostility toward political opponents) has been found to increase user engagement [6, 18, 19, 24]. However, it is largely unclear to what extent these findings translate to short-form video platforms like TikTok, which operate under high levels of algorithmic curation [25], different demographics [26], and audio-visual storytelling [27]. Despite TikTok's growing role in political campaigning, especially among younger voters [28], research on the platform is scant. The few existing studies in this direction have primarily focused on exploratory analyses of metadata (e.g., engagement or follower data [29–31]) or small-scale content analyses based on manually labeled samples [28, 32–35]. For instance, existing work suggests that political actors on TikTok frequently attempt to denigrate political opponents [34] or foster partisanship [31]. Yet, systematic empirical evidence on what content drives engagement in political communication on short-form video platforms is missing.

Here, we analyzed a comprehensive dataset consisting of N = 25,292 TikTok videos posted by German politicians, political parties, and parliamentary groups in the run-up to the 2025 German federal election. This snap election followed a turbulent political period in Germany marked by the collapse of the previous center-left coalition in late 2024, and resulted in historic gains for far-right and far-left parties – especially among young demographics [36]. We implemented (and manually validated) a computational content analysis approach based on large language models (LLMs) to code each video for a wide range of content features, including *Sentiment* (i.e., positive, neutral, or negative), discrete emotions (e.g., *Anger*, *Fear*), and group-oriented messaging such as *Identity Language*, *Relatability*, and *Outgroup Animosity*. We then estimated multilevel regression models to assess which content characteristics were associated with higher levels of engagement on TikTok.

Our study contributes to research and ongoing debates about the electoral incentive dynamics in political communication on short-form video platforms. We demonstrated that videos featuring divisive rhetoric, especially those conveying *Negative Sentiment*, *Anger*, *Disgust*, or *Outgroup Animosity*, attract higher levels of engagement on TikTok. In contrast, content embedding *Positive Sentiment*, *Relatability*, or *Identity Language* performs significantly worse. Furthermore, we found that extreme parties (on both sides of the po-

litical spectrum) were both more likely to post divisive content and more successful in generating engagement compared to their centrist counterparts. Our findings have important implications for democratic discourse, the strategic incentives that shape political communication, and how young voters encounter politics in the video-first age.

2 Background

This section reviews two strands of literature that inform our analysis. First, we review research on affective polarization and populist communication, highlighting how emotions and out-group rhetoric shape contemporary political conflict online. Second, we review prior work on drivers of engagement in political communication on social media.

2.1 Affective polarization and populist communication

Political polarization refers to the extent to which people are divided in their attitudes, identities, and evaluations of opposing groups [37]. Prior work distinguishes affective polarization from ideological polarization, emphasizing that while ideological polarization concerns differences between policy positions and issue preferences, affective polarization is rooted in emotion and group identity that extend beyond party affiliation per se [38–40]. These two forms of polarization are related rather than independent. When political actors hold similar ideological positions, they tend to be evaluated more similarly, whereas greater ideological distance is associated with increasingly polarized affective judgments [41, 42]. Affective polarization is particularly salient on social media, where political interaction is shaped by platform affordances and selective visibility of content [43, 44].

Affective polarization highlights the role of both emotions and group identity in political conflict. First, emotions shape how political conflict is expressed online, influencing how topics are perceived and evaluated and how information and events are processed [40, 45, 46]. Second, group identity structures the direction of these emotional responses. Interactions among in-group members tend to be more positive, whereas communication directed toward out-group members is more negative [19, 47, 48]. Selective exposure and interaction with like-minded others can further reinforce shared preferences and emotional orientations over time, contributing to increasingly homogeneous group behavior [18].

Affective polarization is often leveraged by populist communication, which frames politics as a moral struggle between a virtuous in-group, often described as 'the people', and the negatively portrayed out-group [49, 50]. In many contexts, the primary out-group is 'the elite', and parties outside government are generally more inclined to employ anti-elitist rhetoric given their institutional incentives to criticize those in power [51, 52]. The political elite invoked in populist discourse can take various forms, including political actors, economic elites, multinational corporations, media organizations, or additional groups defined along cultural or national lines [53–55]. In populist communication, emotions and negativity in particular serve as a central stylistic resource that links affective polarization to political messaging. By combining emotionally charged language with group-based distinctions, populist rhetoric translates affective divisions into simplified antagonistic narratives that are well suited to social media environments [52, 56, 57]. From this perspective, out-group animosity and emotional expression are not incidental features of populist communication but core mechanisms through which affective polarization is articulated in online political discourse.

2.2 Drivers of engagement on social media

Political communication on social media is shaped by strategic considerations related to visibility and user engagement. Unlike traditional news media, social media platforms allow political actors to communicate directly with voters, monitor audience reactions in real time, and adapt their messaging accordingly, creating feedback loops between communication and engagement [58–60]. User engagement, in turn, increases the visibility and diffusion of political content and has been linked to political mobilization, including higher voter turnout [61–63].

Prior research analyzing drivers of engagement in online political communication has largely focused on primarily text-based social media platforms (e.g., X/Twitter, Facebook) and has been predominantly centered on the U. S. context. Across these settings, research has shown that sentiment and emotions play a key role in shaping engagement on social media [23, 45, 64, 65]. While positive campaign messages can increase name recognition and highlight personal strengths [66–69], negative communication strategies, such as attacks on political opponents, tend to attract greater attention by eliciting arousing negative emotions [22, 70, 71]. Consistent with this pattern, negative messages are more likely to be shared on platforms such as Facebook and X/Twitter [65, 72], particularly when originating from political actors [73, 74].

Beyond emotional tone, engagement on social media is also shaped by the extent to which political communication activates shared social identities [46]. Identity-based rhetoric, such as the use of collective pronouns like 'we' and 'us,' frames political messages as signals of in-group belonging and inclusion [16]. Such cues have been shown to increase likes and reposts on X/Twitter as well as shares and likes on Facebook [17, 75]. In a similar vein, communication that emphasizes relatability, for example by highlighting ordinariness or personal experiences, reduces perceived social distance between political actors and their audiences [76, 77]. This perceived closeness fosters trust and identification, and plays an important role in shaping engagement [78–80]. At the same time, social media can sharpen boundaries between in-groups and out-groups, and content expressing hostility toward out-groups tends to receive higher levels of sharing on platforms such as X/Twitter and Facebook [19, 44].

Only a few studies have analyzed political communication on TikTok. These works suggest that political actors strategically leverage platform affordances, such as algorithmic recommendation systems and short-video formats, often adopting more emotionally charged and polarizing communication styles associated with higher engagement [28, 81]. An empirical study of right-wing political communication on TikTok in Germany shows that the content of such actors often centers on anti-elite narratives and issues framed as concerns of "ordinary people," such as inflation or war [82]. More explicitly identity-based content (e.g., narratives targeting migrants or political opponents), while less prevalent overall, tends to receive comparatively higher levels of engagement and visibility [82].

Research gap: Existing research on engagement in political communication has largely focused on text-based social media platforms such as X/Twitter and Facebook. However, large-scale empirical evidence on what content characteristics are associated with engagement on short-form video platforms such as TikTok is scant, particularly outside the U. S. political context. In this study, we use computational content analysis to examine how a wide range of content characteristics (i.e., sentiment, discrete emotions, and group-oriented messaging) are associated with user engagement on TikTok during the 2025 Ger-

man federal election. By doing so, our findings inform debates about political discourse, the strategic incentives shaping political communication, and how younger audiences encounter political content in the video-first age.

3 Methods

3.1 Data collection

To systematically identify relevant TikTok accounts, we used a precompiled dataset monitoring the social media activities of German politicians and parties [83]. We filtered the list to include all active TikTok accounts belonging to German politicians who held office during our observation period in the national parliament, state parliaments, or the European Parliament. Additionally, we included active accounts of major political parties, defined as those represented in the most recent German national parliament (*i.e., CDU/CSU, SPD, Die Grüne, Die Linke, FDP, AfD*). The final dataset included a total of 727 active TikTok accounts. To ensure accuracy and validity, we manually verified a random sample of 10% of the accounts and confirmed that all belonged to the indicated political figures.

Using the TikTok Research API [84], we then collected all videos posted by these accounts in the period from May 1, 2024, until the federal election day on February 23, 2025. To avoid capturing post-election content, we ended data collection at 6 pm on election day, when polls officially closed. For each video, we retrieved video metadata, including the video IDs, video length, username, hashtags, video description, automatic transcriptions, as well as engagement metrics, namely, the number of likes, comments, shares, and views. This procedure yielded a final collection of 25,292 TikTok videos. We downloaded the corresponding video files using a custom crawler script based on `yt-dlp` [85].

To analyze the video content, we used `Whisper`, an open-source automatic speech recognition system, to transcribe the audio content of the video files [86, 87]. The resulting transcripts were then used to extract various content features (see next section). In addition, we measured three key structural characteristics of each video: (i) video *Duration* (in seconds), (ii) *Language Complexity*, measured using the Gunning-Fog index [88, 89], and (iii) speaking *Pace*, calculated as the number of words divided by the video's duration [90, 91].

3.2 Content annotation

The video transcripts served as the basis for extracting various content features. Specifically, we annotated each transcript for the *Sentiment* [22, 92], discrete *Emotions* [22, 92], and three group-oriented messaging variables: *Identity Language* [75, 93], *Outgroup Animosity* [24, 94], and *Relatability* [79, 80]. All annotation procedures followed best practices in natural language processing for behavioral science [92].

Sentiment: We used the model *tabularisai/multilingual-sentiment-analysis* to classify each sentence in the transcripts into one of five sentiment categories: 'very negative' (assigned a score of –2), 'negative' (–1), 'neutral' (0), 'positive' (1) or 'very positive' (2). To calculate a video-level sentiment score, we computed the arithmetic mean of the sentence-level scores. For better interpretability and to enable comparison with other categorical content features, we transformed the resulting scores into a categorical variable. Specifically, we coded videos as 'negative' (mean below –0.5), 'neutral' (mean between –0.5 and 0.5), or 'positive' (mean greater than 0.5). As a robustness check, we also repeated our analysis with continuous sentiment scores. Here, we found consistent results (see SI, Supplement E).

Discrete emotions: For emotion extraction, we employed an updated version of the model by [95], namely *tweedmann/pol_emo_mDeBERTa2*. This model is fine-tuned to predict the probability of eight discrete emotions: *Anger*, *Disgust*, *Enthusiasm*, *Fear*, *Hope*, *Joy*, *Pride*, and *Sadness* in political German-language text. Each sentence was assigned a probability for each emotion, and emotions were considered present if their probability exceeded a threshold of 0.65 [95]. At the video level, an emotion was considered present (= 1) if it appeared in at least one sentence (otherwise = 0). We also tested an alternative aggregation approach (i.e., calculating mean emotion scores across sentences). Here, we found consistent results (see SI, Supplement E).

Group-oriented messaging: To identify the presence of *Identity Language*, *Outgroup Animosity*, and *Relatability* in the videos, we employed a large language model (LLM)-based annotation approach. Specifically, we deployed an OpenAI Assistant (based on *gpt-4-turbo*) configured to act as a "professional annotator specializing in political discourse analysis". To guide the annotation, the assistant was provided with detailed definitions of the three variables. The variables identity language and outgroup animosity were coded as binary (i.e., T/F), while relatability was coded as a three-level categorical variable (i.e., low, medium, high). A full version of the annotation prompt is provided in the SI, Supplement B.

User study: We conducted two complementary user studies to validate the automated identification of content features (see SI, Supplement C for details). First, we assessed the reliability of feature detection by conducting a user study on Prolific. Twenty native-speaking participants were recruited and presented with a randomly selected sample of 100 videos. For each video, they were asked to indicate whether it contained any of the content features annotated by the LLM. All participants had at least a bachelor's degree and reported German as their first language (9 females and 11 males with a mean age of 39.55 years). Participants were 1.8 times to 7.7 times more likely to report a content feature as present when the LLM had labeled the video as containing it, compared to when it had labeled it as not containing it. Across all content characteristics, the differences were statistically significant (all $p < 0.05$) and accompanied by moderate to high agreement among raters (ICC ranging from 0.345 to 0.895). Second, we conducted a pairwise comparison to examine whether the LLM also captures relative differences in how strongly the features are expressed. Two trained human coders were presented with 25 video pairs per feature (600 videos in total), and indicated which video expressed the respective feature more strongly. Across all features, coders exhibited high agreement rates (ranging from 0.82 to 0.94) and strong interrater reliability (Cohen's κ ranging from 0.75 to 0.94). Taken together, these two user studies demonstrate that the LLM-based annotations align with human judgments both in terms of feature detection and pairwise comparisons of feature expression.

3.3 Regression analysis

We implemented hierarchical regression models with user-specific random effects to estimate how content characteristics were linked to user engagement with political videos on TikTok. This modeling approach allowed us to account for both the fixed effects of content-level variables and unobserved heterogeneity across user accounts (e.g., varying social influence).

In our analysis, we focused on four engagement outcomes (i.e., dependent variables): the number of (i) likes, (ii) comments, (iii) shares, and (iv) views. Given that the variance of

each of these engagement metrics was higher than their mean, an adjustment for overdispersion was necessary. Following best practices [96], we thus employed negative binomial regression models to explain the four engagement measures. Each outcome variable was modeled separately. For each, we estimated two variants: one that included political *Party* affiliation and the other that included ideological *Alignment* (i.e., left vs. right) as predictors, resulting in a total of eight model specifications.

Our primary explanatory variables were the content features extracted from the video transcripts. These included the *Sentiment* (i.e., negative, neutral [reference], positive), binary indicators for eight discrete emotions (i.e., *Anger*, *Disgust*, *Enthusiasm*, *Fear*, *Hope*, *Joy*, *Pride*, *Sadness*), and three variables capturing group-oriented messaging: *Outgroup Animosity* (= 1 if present, otherwise 0), *Identity Language* (= 1 if present, otherwise 0), and *Relatability* (i.e., low [reference], medium, high).

We further controlled for several structural features of the videos, namely, *Language Complexity* (measured using the Gunning-Fog index), speaking *Pace* (measured in words per second), and video *Duration* (in seconds). To account for temporal variation (e.g., growth of follower bases, and differences in account age), we included monthly fixed effects (i.e., *Month*). All continuous predictors were z-standardized to facilitate interpretability.

Based on these variables, we specified the following regression model:

$$\begin{aligned}
&\log(E(\mathrm{Y}_{ij}|\mathrm{X}_{ij})) \\
&\quad = \beta_0 + \beta_1\,\mathrm{Sentiment}_{ij} + \beta_2\,\mathrm{Anger}_{ij} + \beta_3\,\mathrm{Disgust}_{ij} + \beta_4\,\mathrm{Enthusiasm}_{ij} \\
&\qquad + \beta_5\,\mathrm{Fear}_{ij} + \beta_6\,\mathrm{Hope}_{ij} + \beta_7\,\mathrm{Joy}_{ij} + \beta_8\,\mathrm{Pride}_{ij} + \beta_9\,\mathrm{Sadness}_{ij} \\
&\qquad + \beta_{10}\,\mathrm{OutgroupAnimosity}_{ij} + \beta_{11}\,\mathrm{IdentityLanguage}_{ij} + \beta_{12}\,\mathrm{Relatability}_{ij} \\
&\qquad + \beta_{13}\,\mathrm{PoliticalOrientation}_{ij} + \beta_{14}\,\mathrm{LanguageComplexity}_{ij} + \beta_{15}\,\mathrm{Pace}_{ij} \\
&\qquad + \beta_{16}\,\mathrm{Duration}_{ij} + \beta_{17}\,\mathrm{Month}_{ij} + \mathrm{u}_j.
\end{aligned} \tag{1}$$

In Equation (1), Y_{ij} denotes the outcome (i.e., the number of likes, comments, shares, or views) for video i from account j, X_{ij} is the vector of explanatory variables, β_0 represents the intercept, and u_j are the account-specific random effects. The term $PoliticalOrientation_{ij}$ is a placeholder for either political *Party* affiliation or ideological *Alignment*, which are included in separate model specifications. In the political *Party* models, *SPD* (i.e., the incumbent party) is used as the reference category, with additional categories for the other parties (i.e., *Die Linke*, *Grüne*, *CDU/CSU*, *FDP*, and *AfD*). In the ideological *Alignment* models, *Center-Left* serves as the reference, with *Far-Left*, *Center-Right*, and *Far-Right* as additional categories.

We estimated all models using maximum likelihood estimation with the `glmmTMB` package in R 4.3.0.

4 Empirical analysis

4.1 Posting activity and content characteristics

We used the TikTok Research API to collect all videos posted by accounts of German politicians (members of the national, state, or European parliaments), political parties, and parliamentary groups with an active TikTok account from May 1, 2024, until February 23,

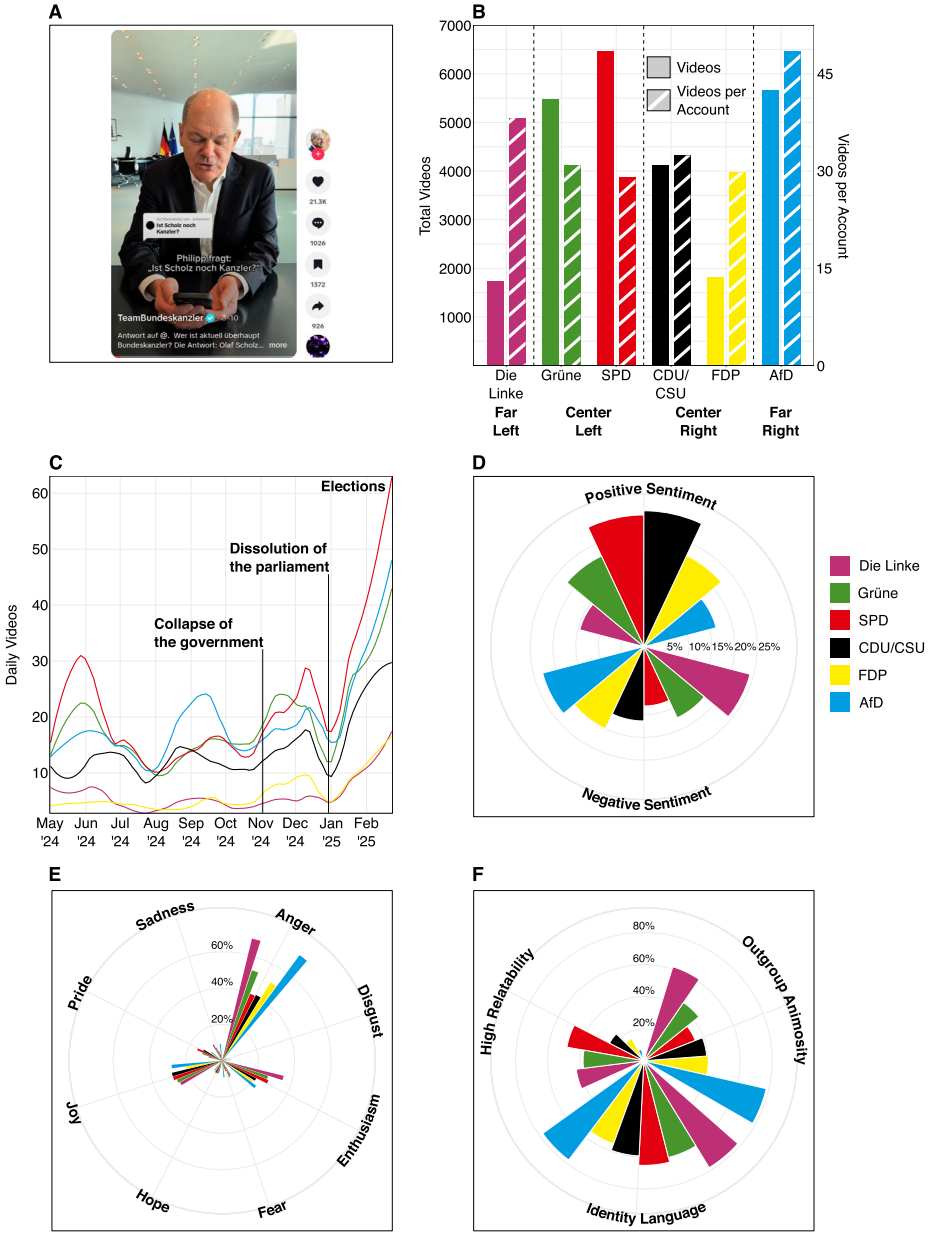


Figure 1 Data overview. (A) An example of a campaign post on TikTok during the 2025 German federal election. **(B)** Number of TikTok posts per political party and the average number of videos per account in our observation period from May 1, 2024 to February 23, 2025. **(C)** The daily number of videos per party. **(D)** The share of posts (in %) per party expressing positive and negative *Sentiment*. **(E)** The share of posts (in %) per party expressing discrete *Emotions*. **(F)** The share of posts (in %) per party expressing *Outgroup Animosity*, *Identity Language*, and *High Relatability*. Additional descriptive statistics are in Supplement A

2025, i.e. during the nine months leading up to the German federal election (see Fig. 1A for an example). In total, the dataset comprised 25,292 videos from 727 distinct accounts, 74.07% of which were published by individual politicians (see Methods). The highest view counts for individual politicians were recorded for the accounts from then-Chancellor Olaf Scholz (≈ 9.14 million), Die-Linke lead candidate Heidi Reichinnek (≈ 7.13 million), and AfD lead candidate Alice Weidel (≈ 6.82 million).

Figure 1B illustrates both the total volume of political video content (left axis) and the average number of videos per account (right axis) produced by German political parties between May 2024 and February 2025. The center-left *SPD* (i.e., the incumbent party) published the highest volume of videos, totaling 6473, followed by the far-right *AfD* with 5665 videos. This surpassed the output from the center-right bloc, i.e., *CDU/CSU* (4118 videos) and *FDP* (1814 videos). *Die Linke*, Germany's primary far-left party, posted the fewest TikTok videos (1734). In terms of posting frequency per account, *AfD* was the most active, averaging 50 videos per account. *Die Linke* followed with an average of 40 videos across its 44 active accounts. Other parties averaged around 30 videos per account.

The video posting activity was closely tied to key political developments, with noticeable spikes following the collapse of the government in October 2024 and a surge after the dissolution of parliament in December 2024. Posting frequency also increased in the lead-up to several elections, including the European parliament election in June 2024, the regional election in three federal states (i.e., Brandenburg, Saxony, and Thuringia) in September 2024, and the federal election in February 2025, which marked the overall peak in activity (see Fig. 1C). This temporal pattern suggests that political video production was highly responsive to institutional crises and the electoral timeline.

Using a (manually validated) computational content analysis approach (see Methods), we coded each video for *Sentiment* (i.e., positive, neutral, or negative), discrete emotions (e.g., *Anger*, *Fear*), and different forms of group-oriented messaging (i.e., *Identity Language*, *Relatability*, *Outgroup Animosity*). Analysis of sentiment revealed systematic differences between political camps. Politicians from centrist parties (i.e., *CDU/CSU, SPD, Grüne, FDP*) were more likely to produce positively valenced content than those at the extremes, namely *Die Linke* and *AfD* (see Fig. 1D). The proportion of positive videos was 25% for centrist, compared to around 15% for extreme parties. In comparison, less than 20% videos from centrist parties were negatively valenced, with the *SPD* exhibiting the lowest proportion at 13%, suggesting a more optimistic messaging strategy. Extreme parties featured higher shares of negative sentiment. Specifically, 24% of videos from *Die Linke* and 23% of videos from *AFD* were negative, consistent with more critical or oppositional narratives.

An analysis of discrete emotions further underscored these differences. Across all parties, *Anger* was the most dominant discrete emotion, but it appeared at roughly twice the rate in content from extreme parties (see Fig. 1E). The *AfD* showed the highest overall prevalence, with over 72% of videos expressing *Anger* (compared to e.g., 40% for the *SPD*). In contrast, centrist parties conveyed more *Hope* and *Pride* than extreme parties, with relative frequencies of more than 7% for *Hope* (vs. 6% for extreme parties) and 11% for *Pride* (vs. 7% for extreme parties), thereby signaling a more prosocial emotional tone.

Group-oriented messaging also varied systematically across political parties (see Fig. 1F). Posts from extreme parties exhibited substantially higher levels of *Outgroup Animosity* compared to more moderate parties. Specifically, approximately 78% of *AfD* videos and 61% of *Die Linke* videos contained *Outgroup Animosity*, which was substantially higher than the overall average of 49% across all parties. Both the *AfD* and *Die Linke* also exhibited elevated use of *Identity Language*, with both parties' shares being around 78%. Relatable content was most common among left-leaning parties, with *SPD*, *Grüne*, and *Die Linke* posting relatable videos in 48%, 37%, and 42% of cases, respectively.

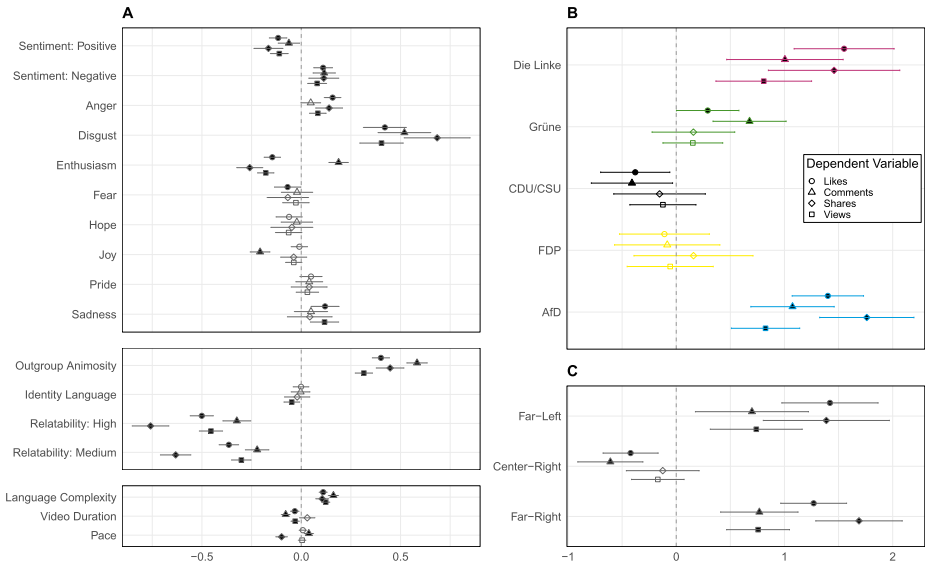


Figure 2 Estimation results. Multilevel negative binomial regression estimating the effects of **(A)** content characteristics (sentiment, discrete emotions, social identification), **(B)** political party, and **(C)** political alignment on the number of likes (circle), comments (triangle), shares (diamond), and views (square) on TikTok. Shown are the coefficient estimates with 95% CIs. Account-specific random effects and monthly fixed effects are included. Full estimation results are in Supplement E

Taken together, these findings indicate clear affective and rhetorical distinctions between political camps: incumbent and center-left parties emphasized positive sentiment and relatable messaging, whereas extremist parties relied more heavily on emotional negativity, outgroup-focused rhetoric, and expressions of *Anger*.

4.2 Drivers of engagement

We estimated multilevel negative binomial regression models to examine how content features (i.e., sentiment, discrete emotions, and group-oriented messaging) were linked to engagement with videos on TikTok, as measured by the number of likes, comments, shares, and views (see Methods). The models controlled for the political orientation of the video's author and structural features of the videos (language complexity, pace, and duration). To account for unobserved heterogeneity and temporal variation in platform dynamics, we additionally included account-specific random intercepts and month fixed effects. Figure 2 visualizes the coefficient estimates for the main explanatory variables; full estimation results are in SI, Supplement S4.

Across all outcome variables, videos expressing *Negative Sentiment* were associated with significantly higher engagement. Relative to neutral content, they received $e^{0.110} - 1 \approx 11.6\%$ more likes (coef: 0.110, $p < 0.001$), 12.3% more comments (coef: 0.116, $p < 0.001$), 12.1% more shares (coef: 0.114, $p < 0.001$), and 8.3% more views (coef: 0.080, $p < 0.001$). In contrast, videos with *Positive Sentiment* received 10.9% fewer likes (coef: −0.116, $p < 0.001$), 6.0% fewer comments (coef: −0.062, $p < 0.001$), 15.2% fewer shares (coef: −0.165, $p < 0.001$), and 10.5% fewer views (coef: −0.111, $p < 0.001$). Overall, this implied that negatively valenced political content was more likely to attract engagement on TikTok during the 2025 German federal election than either neutral or positively valenced content.

The results for discrete emotions mirrored those observed for negative versus positive sentiment. For the group of negatively valenced emotions, the largest effect size was observed for *Disgust*, which was linked to 52.3% more likes (coef: 0.421, $p < 0.001$), 68.0% more comments (coef: 0.519, $p < 0.001$), 98.4% more shares (coef: 0.685, $p < 0.001$), and 49.8% more views (coef: –0.404, $p < 0.001$). Similarly, the presence of *Anger* predicted 17.1% more likes (coef: 0.158, $p < 0.001$), 15.0% more shares (coef: 0.140, $p < 0.001$), and 8.8% more views (coef: 0.084, $p < 0.001$), but showed no significant effect for comments ($p > 0.05$). *Sadness* was also associated with 12.8% more likes (coef: 0.120, $p < 0.001$) and 12.5% more views (coef: 0.118, $p < 0.01$), but showed no significant effects for comments ($p > 0.05$) or shares ($p > 0.05$). *Fear* was linked to 6.7% fewer likes (coef: –0.069, $p < 0.05$), but had no significant effect on other engagement measures. In contrast, positively valenced emotions were largely associated with lower engagement. *Joy* significantly decreased the number of comments a video received by 18.7% (coef: –0.207, $p < 0.001$), and showed no significant reductions across other metrics (each $p > 0.05$). *Enthusiasm* displayed a mixed pattern: while it was associated with 20.8% more comments (coef: 0.189, $p < 0.001$), it corresponded to lower values across the remaining outcomes, including 13.5% fewer likes (coef: –0.145, $p < 0.001$), 22.8% fewer shares (coef: –0.259, $p < 0.001$), and 16.3% fewer views (coef: –0.178, $p < 0.001$). No statistically significant effects were observed for *Hope*, and *Pride* across any engagement metric (each $p > 0.05$). Taken together, these findings suggested that negative emotional appeals were more likely to elicit engagement on TikTok than positive ones.

The presence of group-oriented messaging was also associated with differences in engagement outcomes. Compared to videos with *Low Relatability*, videos with *Medium Relatability* received 30.6% fewer likes (coef: –0.365, $p < 0.001$), 19.9% fewer comments (coef: –0.222, $p < 0.001$), 46.8% fewer shares (coef: –0.632, $p < 0.001$), and 26.0% fewer views (coef: –0.302, $p < 0.001$). *High Relatability* showed even larger reductions, including 39.4% fewer likes (coef: –0.501, $p < 0.001$), 27.8% fewer comments (coef: –0.326, $p < 0.001$), 53.2% fewer shares (coef: –0.760, $p < 0.001$), and 36.5% fewer views (coef: –0.455, $p < 0.001$). *Identity Language* (e.g., references to shared group membership) was significantly associated with 4.7% fewer views (coef: –0.048, $p < 0.05$), but showed no significant effect on any other engagement metric (each $p > 0.05$). In contrast, *Outgroup Animosity* (e.g., expressions of hostility or negative attitudes toward other groups) was associated with 49.3% more likes (coef: 0.401, $p < 0.001$), 79.2% more comments (coef: 0.583, $p < 0.001$), 56.6% more shares (coef: 0.448, $p < 0.001$), and 37.2% more views (coef: 0.316, $p < 0.001$). Overall, these findings implied that content emphasizing group division was more likely to elicit engagement than content appealing to belonging (i.e., *Relatability* and *Identity Language*) during the 2025 German federal election.

Beyond content characteristics, political affiliation was also strongly associated with variation in engagement. Politicians from the two ideologically extreme parties in Germany, *Die Linke* and *AfD*, consistently outperformed those from centrist parties. On average, compared to videos posted by *SPD* politicians, videos from *Die Linke* politicians received 371.6% more likes (coef: 1.551, $p < 0.001$), 172.9% more comments (coef: 1.004, $p < 0.001$), 329.4% more shares (coef: 1.459, $p < 0.001$), and 124.5% more views (coef: 0.809, $p < 0.001$). Similarly, videos from *AfD* politicians received 206.0% more likes (coef: 1.401, $p < 0.001$), 192.7% more comments (coef: 1.074, $p < 0.001$), 482.0% more shares (coef: 1.761, $p < 0.001$), and 128.2% more views (coef: 0.825, $p < 0.001$), relative to *SPD*. In con-

trast, the observed differences between *SPD* and the other centrist parties (i.e., *CDU/CSU, FDP, Grüne*) were rather small and largely not statistically significant (see Fig. 2B). These patterns were further confirmed when controlling for ideological alignment instead of party affiliation (see Methods). Also with this model specification, videos from both *Far-Left* and *Far-Right* accounts received significantly more likes, comments, shares, and views compared to videos from *Center-Left* oriented accounts (each $p < 0.001$; see Fig. 2C).

Our models also accounted for potentially confounding variables, namely, *Language Complexity*, *Duration*, and *Pace*. We found that higher *Language Complexity* was associated with more likes, comments, shares, and views (each $p < 0.001$). In contrast, longer *Duration* was linked to fewer likes ($p < 0.01$) and views ($p < 0.01$), as well as fewer comments ($p < 0.001$). The *Pace* of a video showed a negative and significant effect on comments ($p < 0.01$) and shares (both $p < 0.001$), but not on likes or views. Notably, however, the effect sizes for these control variables were comparatively small (see Fig. 2).

Multiple exploratory analyses extended our results and confirmed their robustness (see Supplement E). First, we assessed multicollinearity by calculating the variance inflation factor (VIF) for all explanatory variables separately for each outcome and political affiliation variable. All VIFs remained below the critical threshold of four (see Table S5). Second, we estimated an implausible model using the number of *XYZ* in each transcript as an explanatory variable [92]. Across all outcome variables, implausible models resulted in higher AIC values (i.e., lower model adequacy) and effect sizes close to zero (see Table S6). Third, we repeated our analysis with continuous measures for *Sentiment* and *Emotion*, which yielded consistent results (see Table S7). Fourth, we implemented a zero-inflated beta regression using the number of likes, comments, and shares per view as the dependent variables (see Table S8), thereby distinguishing active engagement (i.e., likes, comments, and shares) from passive engagement (i.e., views without likes, comments, or shares). Here, we found that especially moralized language, such as *Outgroup Animosity*, *Identity Language*, *Anger*, and *Disgust*, were among the strongest predictors of active engagement. In contrast, low arousal emotions such as *Hope* and *Sadness* were either negatively associated or not statistically significant. Altogether, our exploratory analyses provided confirmatory evidence that negative and divisive messaging was more effective than appeals to belonging in driving engagement on TikTok during the 2025 German federal election.

5 Discussion

Here, we analyzed a comprehensive dataset consisting of $N = 25{,}292$ TikTok videos posted by German politicians, political parties, and parliamentary groups in the run-up to the 2025 German federal election. We found that videos featuring divisive rhetoric, especially those conveying *Negative Sentiment*, *Anger*, *Disgust*, or *Outgroup Animosity*, attract higher levels of engagement on TikTok. In contrast, content emphasizing positive emotion through *Positive Sentiment*, *Identity Language*, or *Relatability* performed significantly worse. Moreover, we observed that extreme parties (on both sides of the political spectrum) were both more likely to post divisive content and more successful in generating engagement compared to their centrist counterparts. Taken together, these findings shed light on the strategic incentives that shape political communication in the video-first era and suggest that divisive content tends to receive higher engagement than unifying content on TikTok, thereby potentially advantaging extreme actors who are more inclined to adopt such messaging strategies.

Prior research on online political communication has largely focused on primarily text-based social media platforms (e.g., X/Twitter, Facebook) and the political context of the U. S. [19, 94, 97–100]. Concordant with the majority of these works, we found that negative and divisive content was particularly likely to go viral on TikTok during the 2025 German federal election. Our results also reinforce prior evidence [19] on the virality of moral emotions (e.g., *Anger*, *Disgust*, and *Outgroup Animosity*) on social media – which showed the strongest positive effects on engagement in our dataset. At the same time, our results challenge common notions often drawn from adjacent fields such as influencer marketing: we found that content emphasizing *Relatability* – typically considered a key driver of engagement [79, 80] – was associated with the strongest negative effect on engagement. A plausible explanation may lie in perceived authenticity. While audiences tend to relate to influencers who appear similar to themselves, politicians are often seen as strategic actors [101], which may make their attempts at relatability seem insincere or performative rather than authentic [102]. This highlights the challenges political actors face on short-form video platforms when attempting to align with the expectations of younger demographics.

Our findings point to potentially considerable incentive problems for political actors. If platforms and their algorithms reward divisive content with heightened visibility and engagement, politicians may feel pressured to adopt more extreme, provocative, or polarizing rhetoric. Prior research suggests that such content can have serious negative implications for societies, for example, by fostering anti-democratic attitudes, deepening partisan divides, and reinforcing discrimination against marginalized groups [43, 103–106]. At the same time, unifying communication strategies (e.g., positive sentiment, relatable narratives) are disincentivized. Concerningly, this incentive structure, favoring divisive over unifying content, creates a potential asymmetric advantage for extremist parties, which are often more willing to exploit this logic. In contrast, moderate parties, which are typically more constrained by norms of civility and democratic responsibility [107], face greater difficulty achieving comparable visibility and engagement. This asymmetry poses the risk of further accelerating political radicalization in digital societies.

As with all research, ours is not free of limitations and offers opportunities for future research. First, our findings are based on observational data and we therefore refrain from making causal claims. Higher engagement with divisive content may reflect algorithmic amplification rather than party strategies alone, and our analysis cannot determine whether such content drives engagement or is selectively promoted by the platform. Future research could use (quasi-)experimental designs to disentangle algorithmic effects from genuine user preferences, though such efforts may be constrained by limited data access. Second, our analysis focuses on a single short-form video platform (i.e., TikTok) and the political context of Germany. While this complements earlier work [19, 94, 97–100] centered on text-based platforms (e.g., X/Twitter, Facebook) and the U. S. political landscape, further research is needed to examine how our findings translate to other short-form video platforms and political contexts (e.g., in the Global South [97, 108]). Third, our analysis focuses on how political messages are communicated rather than on the substantive demands or normative positions they advance. For example, although the AfD and Die Linke are located at opposite ends of the ideological spectrum in Germany, they differ in their political and institutional context (e.g., the AfD has been subject to monitoring by Germany's domestic intelligence service [109]). Our LLM-based content annotation

approach does not capture differences in targeted out-groups or underlying motivations for divisive language, and similarities in rhetorical style should therefore not be interpreted as equivalence in content or intent. Third, our content analysis depends on the accuracy of LLM-based annotations of content characteristics. However, we conducted extensive manual validation, and prior research [92, 110] implies that our approach is an effective tool for psychological content analysis that significantly outperforms methods that have traditionally been used (e.g., dictionary-based approaches). Fourth, our analysis focused on video transcripts and did not include visual elements (e.g., visual sentiment cues). While incorporating such data could potentially enrich the analysis, recent research suggests that text-based approaches often yield similar conclusions, with limited additional insight gained from visual data [111]. Fifth, more research is needed to identify effective interventions that improve political discourse on platforms like TikTok. Potential approaches include media literacy initiatives, greater algorithmic transparency, and platform design changes aimed at reducing the spread of divisive content [112, 113]. Here, a key goal should be to prevent a self-reinforcing cycle, in which even well-meaning political actors feel pressured to adopt more divisive communication strategies.

From a broader perspective, our study raises urgent questions about the growing political influence of short-form video platforms and their algorithmic recommendation systems. Social media, once envisioned as a tool to connect individuals and democratize communication, has evolved into a channel where divisive content gains disproportionate visibility and engagement. This is especially concerning given that platforms like TikTok attract a disproportionately young user base – a key voting demographic that may be particularly vulnerable to this kind of strategically framed political messaging. Ensuring this group has access to accurate and trustworthy information is essential for safeguarding electoral integrity. While we do not claim a causal link between success on TikTok and electoral outcomes, it is striking that the parties most successful on the platform were also the most favored by young voters in the 2025 German federal election [114].

Supplementary information

Supplementary information accompanies this paper at https://doi.org/10.1140/epjds/s13688-026-00632-7.

Additional file 1. (PDF 207 kB)

Author contributions

K.S., C.D., E.D., and N.P. conceived and designed the study. K.S., C.D., and E.D. collected and analyzed the data. K.S., C.D., E.D., and N.P. wrote the manuscript. All authors approved the manuscript.

Funding information

Open Access funding enabled and organized by Projekt DEAL.

Data availability

Code and anonymized data to replicate the results of this study are available through the Open Science Framework (OSF), https://osf.io/jknpx/.

Declarations

Ethics approval and consent to participate

All observational analyses are based on publicly available data. The data collection and the analysis follow common standards for ethical research [115]. Participants in the user studies provided informed consent.

Consent for publication

Not applicable.

Competing interests
The authors declare no competing interests.

Received: 15 September 2025 Accepted: 19 February 2026 Published online: 03 March 2026

References

1. Vázquez-Herrero J, Negreira-Rey M-C, López-García X (2022) Let's dance the news! How the news media are adapting to the logic of TikTok. Journalism 23:1717–1735
2. Newman N (2022) How Publishers Are Learning to Create and Distribute News on TikTok. Tech. Rep., Reuters Institute for the Study of Journalism
3. Zulli D, Zulli DJ (2020) Extending the Internet meme: conceptualizing technological mimesis and imitation publics on the TikTok platform. New Media Soc 24:1872–1890
4. Zannettou S, et al (2024) Analyzing user engagement with TikTok's short format video recommendations using data donations. In: Proceedings of the 2024 CHI conference on human factors in computing systems, pp 1–16
5. Boeker M, Urman A (2022) An empirical investigation of personalization factors on TikTok. In: Proceedings of the ACM web conference 2022, pp 2298–2309
6. Sangiorgio E, Cinelli M, Cerqueti R, Quattrociocchi W (2024) Followers do not dictate the virality of news outlets on social media. PNAS Nexus 3:pgae257
7. Die Bundesbeauftrage für den Datenschutz und die Informationsfreiheit (2024) TikTok. https://www.bfdi.bund.de/DE/Buerger/Inhalte/Telemedien/TikTok.html
8. Statista (2025) TikTok Users in Germany in 2024, by Age Group. https://www.statista.com/statistics/1337425/TikTok-users-age-group-germany/
9. Cheng Z, Li Y (2023) Like, comment, and share on TikTok: exploring the effect of sentiment and second-person view on the user engagement with TikTok news videos. Soc Sci Comput Rev 42:201–223
10. Biswas A, Lin Y-R, Tai YC, Desmarais BA (2025) Political elites in the attention economy: visibility over civility and credibility? In: Proceedings of the international AAAI conference on web and social media, vol 19, pp 241–258
11. Kreiss D (2016) Seizing the moment: the presidential campaigns' use of Twitter during the 2012 electoral cycle. New Media Soc 18:1473–1490
12. Rathje S, Van Bavel JJ (2025) The Psychology of Virality. Trends Cogn Sci
13. Stieglitz S, Dang-Xuan L (2012) Political communication and influence through microblogging—an empirical analysis of sentiment in Twitter messages and retweet behavior. In: 2012 45th Hawaii international conference on system sciences. IEEE, pp 3500–3509
14. Nulty P, Theocharis Y, Popa SA, Parnet O, Benoit K (2016) Social media and political communication in the 2014 elections to the European Parliament. Elect Stud 44:429–444
15. Wollebæk D, Karlsen R, Steen-Johnsen K, Enjolras B (2019) Anger, fear, and echo chambers: the emotional basis for online behavior. Soc Media Soc 5:2056305119829859
16. Steffens NK, Haslam SA (2013) Power through 'us': leaders' use of we-referencing language predicts election victory. PLoS ONE 8:e77952
17. Leach S, et al (2024) Politicians' Use of National Identity Rhetoric on Social Media Predicts Engagement and Electoral Success. PsyArXiv
18. Nettasinghe B, Percus AG, Lerman K (2025) How Out-Group Animosity Can Shape Partisan Divisions: a Model of Affective Polarization. PNAS Nexus pgaf082
19. Rathje S, Van Bavel JJ, van der Linden S (2021) Out-group animosity drives engagement on social media. Proc Natl Acad Sci 118:e2024292118
20. Hackenburg K, Brady WJ, Tsakiris M (2023) Mapping moral language on US presidential primary campaigns reveals rhetorical networks of political division and unity. PNAS Nexus 2:pgad189
21. Törnberg P, Chueri J (2025) Elite Political Discourse Has Become More Toxic in Western Countries. arXiv preprint. arXiv:2503.22411
22. Robertson CE, et al (2023) Negativity drives online news consumption. Nat Hum Behav 7:812–822
23. Stieglitz S, Dang-Xuan L (2013) Emotions and information diffusion in social media—sentiment of microblogs and sharing behavior. J Manag Inf Syst 29:217–248
24. Yu X, Wojcieszak M, Casas A (2024) Partisanship on social media: in-party love among American politicians, greater engagement with out-party hate among ordinary users. Polit Behav 46:799–824
25. Song J, Liu J (2024) A data-driven short video international communication model based on indicator system communication network and attention bilstm neural network. Sci Rep 14:14532
26. Gao Y, Liu F, Gao L (2023) Echo chamber effects on short video platforms. Sci Rep 13:6282
27. Cao H (2025) Exploring the promotion of musical intangible cultural heritage under TikTok short videos. Sci Rep 15:21772
28. Medina Serrano JC, Papakyriakopoulos O, Hegelich S (2020) Dancing to the partisan beat: a first analysis of political communication on TikTok. In: Proceedings of the 12th ACM conference on web science, pp 257–266
29. Guinaudeau B, Munger K, Votta F (2022) Fifteen seconds of fame: TikTok and the supply side of social video. Comput Commun Res 4:463–485
30. Ibrahim H, et al (2025) TikTok's Recommendations Skewed towards Republican Content during the 2024 US Presidential Race. arXiv preprint. arXiv:2501.17831
31. Li Y, Cheng Z, Gil de Zúñiga H (2025) TikTok's Political Landscape: examining Echo Chambers and Political Expression Dynamics. New Media Soc
32. Zeng J, Abidin C (2023) '# okboomer, time to meet the zoomers': studying the memefication of intergenerational politics on TikTok. In: The playful politics of memes. Routledge, pp 93–115
33. Cervi L, Marín-Lladó C (2021) What Are Political Parties doing on TikTok? The Spanish Case. Prof Inf 30
34. Zamora-Medina R, Suminas A, Fahmy SS (2023) Securing the youth vote: a comparative analysis of digital persuasion on TikTok among political actors. Media Commun 11:218–231
35. Moir A (2023) The Use of TikTok for Political Campaigning in Canada: the Case of Jagmeet Singh. Soc Media Soc 9

36. Tagesschau (2025) Stimmanteile bei 18-24-Jährigen im Vergleich zu 2021. https://www.tagesschau.de/wahl/archiv/2025-02-23-BT-DE/charts/umfrage-alter/chart_1862482.shtml
37. Esau K, et al (2024) Destructive polarization in digital communication contexts: a critical review and conceptual framework. Inf Commun Soc 28:1499–1520
38. Iyengar S, Lelkes Y, Levendusky M, Malhotra N, Westwood SJ (2019) The origins and consequences of affective polarization in the United States. Annu Rev Polit Sci 22:129–146
39. Brüggemann M, Meyer H (2023) When debates break apart: discursive polarization as a multi-dimensional divergence emerging in and through communication. Commun Theory 33:132–142
40. Kish Bar-On K, Dimant E, Lelkes Y, Rand DG (2024) Unraveling polarization: insights into individual and collective dynamics. PNAS Nexus 3:pgae426
41. Rogowski JC, Sutherland JL (2016) How ideology fuels affective polarization. Polit Behav 38:485–508
42. Webster SW, Abramowitz AI (2017) The ideological foundations of affective polarization in the US electorate. Am Polit Res 45:621–647
43. Bail CA, et al (2018) Exposure to opposing views on social media can increase political polarization. Proc Natl Acad Sci 115:9216–9221
44. Barberá P (2020) Social media, echo chambers, and political polarization. In: Social media and democracy: the state of the field, prospects for reform. Cambridge University Press, Cambridge
45. Humprecht E, Amsler M, Esser F, Van Aelst P (2024) Emotionalized social media environments: how alternative news media and populist actors drive angry reactions. Polit Commun 41:559–587
46. Settle JE (2018) Frenemies: how social media polarizes America. Cambridge University Press, Cambridge
47. Lerman K, Feldman D, He Z, Rao A (2024) Affective polarization and dynamics of information spread in online networks. npj Complex 1:8
48. Wagner M (2021) Affective polarization in multiparty systems. Elect Stud 69:102199
49. Mudde C (2004) The populist zeitgeist. Gov Oppos 39:541–563
50. Harteveld E, Mendoza P, Rooduijn M (2022) Affective polarization and the populist radical right: creating the hating? Gov Oppos 57:703–727
51. Vaughan M, Heft A (2023) Anti-elitism in the European radical right in comparative perspective. J Common Mark Stud 61:76–94
52. Widmann T (2021) How emotional are populists really? Factors explaining emotional appeals in the communication of political parties. Polit Psychol 42:163–181
53. Fernández García AB, García Luengo Ó (2018) Populist parties in western Europe. An analysis of the three core elements of populism. Commun Soc 31:57–74
54. Schwörer J (2022) Less populist in power? Online communication of populist parties in coalition governments. Gov Oppos 57:467–489
55. Aalberg T, Esser F, Reinemann C, Strömbäck J, Vreese CH (eds) (2017) Populist political communication in Europe Routledge, New York
56. Ernst N, Blassnig S, Engesser S, Büchel F, Esser F (2019) Populists Prefer Social Media over Talk Shows: an Analysis of Populist Messages and Stylistic Elements across Six Countries. Soc Media Soc 5
57. Hameleers M, Schmuck D, Bos L, Ecklebe S (2021) Interacting with the ordinary people: how populist messages and styles communicated by politicians trigger users' behaviour on social media in a comparative context. Eur J Commun 36:238–253
58. Strömbäck J, Kiousis S (2014) Strategic political communication in election campaigns. Polit Commun 1:109–115
59. Papakyriakopoulos O, Hegelich S, Shahrezaye M, Serrano JCM (2018) Social Media and Microtargeting: political Data Processing and the Consequences for Germany. Big Data Soc 5
60. Stieglitz S, Dang-Xuan L (2013) Social media and political communication: a social media analytics framework. Soc Netw Anal Min 3:1277–1291
61. Serrano JCM, Shahrezaye M, Papakyriakopoulos O, Hegelich S (2019) The rise of Germany's AfD: a social media analysis. In: Proceedings of the 10th international conference on social media and society, pp 214–223
62. Gibson RK (2015) Party change, social media and the rise of 'citizen-initiated' campaigning. Party Polit 21:183–197
63. Bond RM, et al (2012) A 61-million-person experiment in social influence and political mobilization. Nature 489:295–298
64. Nelson-Field K, Riebe E, Newstead K (2013) The emotions that drive viral video. Australas Mark J 21:205–211
65. Bene M (2017) Go viral on the Facebook! Interactions between candidates and followers on Facebook during the Hungarian general election campaign of 2014. Inf Commun Soc 20:513–529
66. Helboe Pedersen H (2012) What do parties want? Policy versus office. West Eur Polit 35:896–910
67. Gilardi F, Gessler T, Kubli M, Müller S (2022) Social media and political agenda setting. Polit Commun 39:39–60
68. Kobayashi T, Ichifuji Y (2015) Tweets that matter: evidence from a randomized field experiment in Japan. Polit Commun 32:574–593
69. Bowler S, McElroy G, Müller S (2020) Campaigns and the selection of policy-seeking representatives. Legis Stud Q 45:397–431
70. Dijksterhuis A, Aarts H (2003) On wildebeests and humans: the preferential detection of negative stimuli. Psychol Sci 14:14–18
71. Ceron A, d'Adda G (2016) E-campaigning on Twitter: the effectiveness of distributive promises and negative campaign in the 2013 Italian election. New Media Soc 18:1935–1955
72. Watson J, van der Linden S, Watson M, Stillwell D (2024) Negative Online News Articles Are Shared More to Social Media. Sci Rep 14
73. Trilling D, Tolochko P, Burscher B (2017) From newsworthiness to shareworthiness: how to predict news sharing based on article characteristics. Journal Mass Commun Q 94:38–60
74. Heiss R, Schmuck D, Matthes J (2019) What drives interaction in political actors' Facebook posts? Profile and content predictors of user engagement and political actors' reactions. Inf Commun Soc 22:1497–1513
75. Hopkins DJ, Lelkes Y, Wolken S (2025) The rise of and demand for identity-oriented media coverage. Am J Polit Sci 69:483–500

76. Enli GS, Skogerbø E (2013) Personalized campaigns in party-centred politics: Twitter and Facebook as arenas for political communication. Inf Commun Soc 16:757–774
77. Farkas X, Bene M (2021) Images, politicians, and social media: patterns and effects of politicians' image-based political communication strategies on social media. Int J Press/Polit 26:119–142
78. Wang R, Chan-Olmsted S (2024) Brand Communication through Social Media Influencers: trust Building and Trust Transfer Mechanisms. Int J Bus Commun
79. Atiq M, Abid G, Anwar A, Ijaz MF (2022) Influencer marketing on Instagram: a sequential mediation model of storytelling content and audience engagement via relatability and trust. Information 13:345
80. Liu X, Zheng X (2024) The persuasive power of social media influencers in brand credibility and purchase intention. Humanit Soc Sci Commun 11:1–12
81. Schellewald A (2023) Understanding the popularity and affordances of TikTok through user experiences. Media Cult Soc 45:1568–1582
82. Meyer H, Niemann-Lenz J, Rodeck L, Revers M (2025) Beyond Anti-Elitism and Out-Group Attacks: how Concerns Shape the AfD's Populist Representation on German TikTok during the 2024 European Elections. Inf Commun Soc. Forthcoming
83. Fuchs M (2025) Deutsche Politik Auf Tik Tok. https://docs.google.com/spreadsheets/d/13yIKz_RdUe1IAExjJKiPlgzkD-T0ZXRbEnU2nIkDJFU
84. TikTok (n.d.) TikTok Research API. https://research.TikTok.com. Accessed: 2025-06-26
85. yt-dlp contributors (2021) yt-dlp: a YouTube-dl Fork with Additional Features and Fixes. https://github.com/yt-dlp/yt-dlp
86. OpenAI (2022) Whisper: open Source Automatic Speech Recognition (asr) System. https://github.com/openai/whisper
87. Radford A, Gao JW, Clark T, et al (2022) Robust Speech Recognition via Large-Scale Weak Supervision. https://cdn.openai.com/papers/whisper.pdf
88. Gunning R (1952) The technique of clear writing. McGraw-Hill, New York
89. Solovev K, Pröllochs N (2025) References to Unbiased Sources Increase the Helpfulness of Community Fact-Checks. Sci Rep 15
90. Sihag M, et al (2023) A data-driven approach for finding requirements relevant feedback from TikTok and YouTube. In: 2023 IEEE 31st international Requirements Engineering conference (RE). IEEE, pp 111–122
91. Welbourne DJ, Grant WJ (2016) Science communication on YouTube: factors that affect channel and video popularity. Public Underst Sci 25:706–718
92. Feuerriegel S, et al (2025) Using natural language processing to analyse text data in behavioural science. Nat Rev Psychol 4:96–111
93. Rasmussen J, Rathje S, Van Bavel JJ, Robertson C (2025) Negativity and Identity Language Have Additive Effects on Online News Consumption. OSF Preprint
94. Brady WJ, Wills JA, Jost JT, Tucker JA, Van Bavel JJ (2017) Emotion shapes the diffusion of moralized content in social networks. Proc Natl Acad Sci 114:7313–7318
95. Widmann T, Wich M (2022) Creating and comparing dictionary, word embedding, and transformer-based models to measure discrete emotions in German political text. Polit Anal 31:626–641
96. Hardin JW, Hilbe JM (2007) Generalized linear models and extensions. Stata Press
97. Falkenberg M, Zollo F, Quattrociocchi W, Pfeffer J, Baronchelli A (2024) Patterns of partisan toxicity and engagement reveal the common structure of online political communication across countries. Nat Commun 15:9560
98. Guess AM, et al (2023) How do social media feed algorithms affect attitudes and behavior in an election campaign? Science 381:398–404
99. Dang-Xuan L, Stieglitz S, Wladarsch J, Neuberger C (2017) An investigation of influentials and the role of sentiment in political communication on Twitter during election periods. In: Social media and election campaigns. Routledge, pp 168–198
100. Bossetta M (2018) The digital architectures of social media: comparing political campaigning on Facebook, Twitter, Instagram, and snapchat in the 2016 US election. Journal Mass Commun Q 95:471–496
101. Aalberg T, Strömbäck J, De Vreese CH (2012) The framing of politics as strategy and game: a review of concepts, operationalizations and key findings. Journalism 13:162–178
102. Enli G (2015) Mediated authenticity: how the media constructs reality. Peter Lang Verlag
103. Hartman R, et al (2022) Interventions to reduce partisan animosity. Nat Hum Behav 6:1194–1205
104. Garrett KN, Bankert A (2020) The moral roots of partisan division: how moral conviction heightens affective polarization. Br J Polit Sci 50:621–640
105. Vaidhyanathan S (2018) Antisocial media: how Facebook disconnects us and undermines democracy. Oxford University Press, London
106. Lorenz-Spreen P, Oswald L, Lewandowsky S, Hertwig R (2023) A systematic review of worldwide causal and correlational evidence on digital media and democracy. Nat Hum Behav 7:74–101
107. Gidron N, Hall PA (2020) Populism as a problem of social integration. Comp Polit Stud 53:1027–1059
108. Munzert S, Traunmüller R, Barberá P, Guess A, Yang J (2025) Citizen preferences for online hate speech regulation. PNAS Nexus 4:pgaf032
109. Tagesschau (2025) AfD laut Verfassungsschutz "gesichert rechtsextremistisch". https://www.tagesschau.de/inland/innenpolitik/verfassungsschutz-afd-102.html
110. Rathje S, et al (2024) GPT is an effective tool for multilingual psychological text analysis. Proc Natl Acad Sci 121:e2308950121
111. Chen H, Bisbee J, Tucker JA, Nagler J (2025) Labeling Social Media Posts: does Showing Coders Multimodal Content Produce Better Human Annotation, and a Better Machine Classifier? Polit Sci Res Methods 1–13
112. Milli S, et al (2025) Engagement, user satisfaction, and the amplification of divisive content on social media. PNAS Nexus 4:pgaf062
113. Combs A, et al (2023) Reducing political polarization in the United States with a mobile chat platform. Nat Hum Behav 7:1454–1461

114. Statista (2025) Junge favorisieren AfD und Linke, Alte die Union. https://de.statista.com/infografik/33994/stimmenanteile-bei-der-bundestagswahl-2025-nach-altersgruppen/
115. Rivers CM, Lewis BL (2014) Ethical research standards in a world of big data. F1000Res 3:38

Publisher's note

Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.