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Echoes of Emotion: Influencers' Communication Strategies and Comment Polarization in the US 2024 Presidential Election

Xianquan Zeng [1], Jiarun Du [1], Jinghong Xu [2,3], and Qiong Xu [4]

[1] School of Literature and Journalism, Hunan Polytechnic University, China
[2] School of Journalism and Communication, Beijing Normal University, Beijing, China
[3] International College, Krirk University, Thailand
[4] School of Journalism and Communication, Hunan University, China

Correspondence: Qiong Xu (xuqiong@hnu.edu.cn)

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Abstract

This study examines strategic differences between Democratic and Republican YouTube influencers during the 2024 US presidential election and their association with comment-level political polarization. Drawing on digital opinion leadership theory, platform architecture perspectives, and visual framing research, we employ a mixed-methods design integrating framing analysis with latent Dirichlet allocation topic modeling. The study analyzes 373 videos and 371,124 user comments published between July 27 and November 30, 2024. These data were sourced from 40 YouTube channels with at least 100,000 subscribers. Findings reveal that Democratic creators adopted a moral-crisis framing strategy while Republicans emphasized an opportunity–explanation framing model, and that 56.4% of comment discourse centers on candidate personality rather than policy substance, exhibiting patterns consistent with affective polarization. The study develops and empirically calibrates the YouTube polarization risk assessment scale through ordinary least squares regression analysis ($R^2 = 0.224$, $p < 0.001$), identifying political stance strength and humor/sarcasm as the strongest predictors of comment polarization, thereby providing an exploratory, empirically informed framework for assessing polarization risk in platform-based political communication.

Keywords

affective polarization; electoral communication; polarization; political communication; political influencers; YouTube

1. Introduction

On November 5th, 2024, Donald Trump won the presidential election, signaling both political reconfiguration and transformation in communication studies. What commentators and scholars have characterized as the first truly platform-driven presidential election (Schwemmer & Riedl, 2025; Stocking et al., 2024; Zakrzewski, 2024) witnessed YouTube political influencers transitioning from peripheral commentators to central actors. Marshall McLuhan's "the medium is the message" finds renewed expression in the digital platform era: When political discourse becomes fully integrated into platform logic, influencers emerge as integral elements of politics itself (Gillespie, 2018; McLuhan, 1994).

Pew Research Center data show that approximately half of news influencers on YouTube express clear political leanings (28% lean right, 21% lean left; Stocking et al., 2024). Across social media platforms, 37% of American adults aged 18 to 29 report regularly getting news from influencers, underscoring these creators' significance as political information sources for younger demographics (Stocking et al., 2024). These digitally native political actors contribute to a new paradigm through parasocial relationships, visual narratives, and entertainment-oriented packaging, forming a "horizontal political communication network" where influence derives from authenticity and emotional resonance rather than institutionalized authority (Riedl et al., 2023). YouTube's platform architecture, including its recommendation systems and engagement metrics, shapes political information visibility in ways that prior research has linked to "interest graphs" logic (Haroon et al., 2023; Yu et al., 2024). Unlike X's (formerly Twitter) rapid-scrolling or TikTok's fragmented flows, YouTube's "deep engagement" model fosters immersion in long-form content and comment debates, creating conditions that may both facilitate cross-partisan exposure and concentrate ideologically congruent content (Hosseinmardi et al., 2021).

The 2024 cycle marked the full emergence of a novel political communication ecology, with substantial investments in influencer partnerships leveraging an organic content veneer to shape political discourse (Zakrzewski, 2024). YouTube influencers have perfected "political entertainment," converting complex policy issues into engaging narratives (Beck & Spencer, 2025; Berrocal et al., 2014). This communication model coincides with intensifying American affective polarization where influencers serve as architects of group identity through visual symbols, narrative frameworks, and interactive rituals (Cole et al., 2025; Druckman et al., 2022).

This study dissects divergent communication strategies employed by partisan YouTube influencers during the 2024 presidential election and examines how these strategies are associated with comment-level political polarization within YouTube's platform environment. The findings prompt reconsideration of the public sphere, political participation, and democracy's future, given the ascent of influencers as new opinion leaders within platform-mediated communication environments.

2. Literature Review

2.1. The Rise of Digital Opinion Leaders: From Traditional Elites to Platform-Era Power Reconstruction

The emergence of "proximal mass opinion leaders," new political actors who maintain intimate proximity to their audiences while wielding mass-scale influence, cuts across the traditional binaries of elite versus mass, professional versus amateur, and formal versus informal (Harff et al., 2025).

YouTube political influencers exemplify this new form of power. Their influence is built on three core mechanisms: commercialized content production, strategic platform utilization, and parasocial interactions (Fischer et al., 2022). Unlike traditional elites, their authority derives from "political parasocial relationships" (Cohen & Holbert, 2021) rooted in perceived intimacy rather than institutional position. Followers often credit content based on influencer credibility rather than the merits of the content itself (Rose & Rohlinger, 2024; Turcotte et al., 2015).

These opinion leaders operate within a platform environment in which engagement metrics shape content visibility (Haroon et al., 2023). As Van Dijck et al. (2018) argued, this creates a "platform politics paradox" where the potential for deep engagement coexists with the risk of filter bubbles. Understanding this platform context is essential for analyzing influencer strategies, even though the present study focuses on user-driven content rather than algorithmically boosted recommendations.

2.2. Visual Politics and Entertainment Fusion: YouTube's Political Aesthetics

YouTube's platform affordances, including long-form video hosting, content recommendation systems, comment sections, and subscription features, fundamentally shape the possibilities and constraints of political communication (Evans et al., 2017). These affordances do not determine content but rather create a "grammar" within which influencers strategically construct political meaning (Bucher & Helmond, 2018).

"Politainment," the blending of politics and entertainment that originated in the television era (Nieland, 2008), takes a more complex form on YouTube (Berrocal et al., 2014). Humor has emerged as a core rhetorical strategy that not only lowers barriers to political engagement but also blurs the boundaries between critique and entertainment (Beck & Spencer, 2025). Through meme-like visual simplification, influencers distill complex policy issues into shareable visual symbols, converting ideological conflicts into cultural signifiers (Shifman, 2014).

The integration of verbal and visual framing is particularly salient in the YouTube context where meaning is constructed through the interplay of spoken discourse, on-screen text, and visual imagery. An integrative framing analysis approach recognizes that verbal and visual frames within the same message may differ and interact, necessitating systematic attention to both modalities (Dan, 2017). As visual framing research demonstrates, visual elements carry independent framing power that often elicits stronger affective responses than text alone (Geise & Baden, 2015; Müller & Geise, 2015). This dual-modality character of YouTube's political content necessitates an analytical approach that attends to both verbal and visual dimensions of framing (Rodriguez & Dimitrova, 2011).

2.3. New Mechanisms of Polarization: The Spiral Ascent from Cognitive Divergence to Affective Opposition

This study focuses specifically on affective polarization, defined as the tendency of partisans to view opposing partisans negatively and co-partisans positively (Iyengar & Westwood, 2015), rather than ideological polarization over policy positions. This distinction is critical: While ideological divergence may remain relatively stable, affective polarization has intensified dramatically in recent decades (Iyengar et al., 2019). Within digital platforms, affective polarization manifests as emotional hostility in discursive interactions, making YouTube comment sections a particularly apt site for observing these dynamics.

YouTube comment sections offer a useful window into polarization mechanisms. They exhibit measurable patterns of toxicity polarization where comments cluster into distributions reflecting strong partisan divergence rather than a moderate middle ground (Mall et al., 2024). Sentiment analysis of comments related to recent elections confirms that these sections display higher emotional polarity than the video content itself (Shevtsov et al., 2023).

In social–psychological terms, political polarization operates as a process of group identity, operating through the mechanisms of in-group favoritism and out-group derogation as predicted by social identity theory (Cole et al., 2025; Tajfel & Turner, 2001). Within YouTube's environment, platform features may interact with these psychological mechanisms: recommendation systems, upvoting functions, and subscription features create conditions that can concentrate ideologically congruent content (Hosseinmardi et al., 2021). This dynamic interacts with systematic public misperception of partisan extremity (Druckman et al., 2022), creating a mutually reinforcing cycle between perceived and actual polarization (Yarchi et al., 2024).

2.4. Theoretical Synthesis and Research Gaps

Based on the previous discussion, we can distill several core theoretical frameworks for understanding the communication of political influencers on YouTube and its democratic implications:

First, the digital opinion leadership framework illustrates how political influencers shape political attitudes through parasocial relationships and platform functionalities, employing mechanisms distinct from traditional communication (Harff et al., 2025; Schwemmer & Riedl, 2025). Second, a platform architecture perspective recognizes that structural features of digital platforms, such as engagement metrics and recommendation systems, may systematically shape the visibility and reach of political content (Haroon et al., 2023; Van Dijck et al., 2018), although the present study does not directly measure these processes. Third, visual framing and politainment research demonstrates that political content on YouTube is constructed through the interplay of verbal and visual modalities, where entertainment-oriented packaging and emotional resonance serve as key strategic resources (Beck & Spencer, 2025; Geise & Baden, 2015).

Despite substantial literature on social media political communication, significant gaps remain. First, platform-specific analyses of YouTube's unique ecosystem—particularly the interplay between long-form content, comment sections, and recommendation systems—are scarce. Second, empirical studies directly linking content characteristics to comment-level polarization responses are limited. Third, while mixed methods are established in digital research (Rogers, 2019), studies integrating framing analysis with large-scale topic modeling within YouTube's electoral context remain rare. Existing literature (Freelon et al., 2020) further suggests that right-wing creators may leverage platform affordances more effectively, yet whether partisan strategies converge or diverge within YouTube's environment remains unclear.

To address these gaps, this study proposes the following research questions:

> RQ1: During the 2024 US presidential election, what systematic differences exist in content framing strategies between Democratic and Republican-oriented YouTube political influencers?

RQ2: What is the main topic structure of political discussions related to the 2024 US election on YouTube, and what polarization characteristics does it present?

RQ3: Is there a model that can effectively predict the degree of polarization in YouTube political video comment sections?

3. Research Design and Method

3.1. Research Method Overview

This study employed a mixed-methods approach integrating framing analysis with quantitative latent Dirichlet allocation (LDA) topic modeling. The framing analysis combined qualitative and quantitative elements: The coding scheme was developed inductively through qualitative open coding of a video subsample (Stage 1), and subsequently applied as a systematic quantitative coding instrument to the full corpus (Stage 2). This two-stage approach captures both the nuanced construction of frames within individual videos and their distributional patterns across the partisan spectrum, aligning with established mixed-methods practices in political communication research (Walter & Ophir, 2019; Ylä-Anttila et al., 2022). The LDA component provides a complementary computational perspective on large-scale comment discourse, and its integration with the framing results is examined through cross-tabulation analysis.

3.2. Sample Selection and Data Collection

We conducted systematic searches on the YouTube platform on August 8th 2025, using keywords including "2024 election," "Trump 2024," "Harris," "Democratic," "Republican," "political commentary," "election," "MAGA," and their combined variants, initially identifying content creators with clear political orientations ($n = 53$). These creators clearly stated their political positions in their names, channel descriptions, video content, or social media accounts. The search strategy followed social media mixed-methods design principles, using multiple keyword combinations to ensure sample comprehensiveness and representativeness (Schneiker et al., 2019).

Screening criteria were developed with reference to Fischer et al.'s (2022) framework on YouTube political influencers. First, channels were required to have a minimum of 100,000 subscribers. This criterion was adopted to focus on channels with established audiences large enough to sustain community interaction and potentially amplify partisan messaging, while excluding smaller or more peripheral voices unlikely to shape broader public discourse. Second, relevant political content had to be published during the most intense period of the US presidential election from July 27th to November 30th, 2024, as well as after the election, ensuring temporal relevance. Third, high update frequency had to be maintained during the research period, with at least one video published weekly, ensuring content continuity and timeliness. Additionally, the study excluded current political figures and mainstream media organization accounts, focusing on digitally native political influencers. A total of 35 influencers met these three sampling criteria. An additional five influencers (e.g., Candace Owens) were purposively included given their exceptional content impact, high engagement levels, cross-platform visibility, and prominent role in shaping election-related public discourse. Excluding them did not statistically alter the overall pattern of the findings. These criteria follow Kim et al.'s

(2018) recommendations for social media content analysis sampling methods, ensuring capture of politically significant communication events.

The final sample consisted of 20 Democratic-leaning and 20 Republican-leaning influencers ($N = 40$), with a cumulative subscriber count of 77.7 million (as of August 8th, 2025). From all videos published by these 40 influencers within the target timeframe, irrelevant content (e.g., non-election topics) was removed. A stratified random sampling method was then employed, selecting 8–10 videos per influencer, resulting in a final corpus of 373 valid video samples for analysis (192 Democratic and 181 Republican samples).

Although prior research documented that conservative voices often achieve greater reach and engagement on social media platforms (Freelon et al., 2020; Schradie, 2019), we employed a balanced sample to enable controlled comparative analysis. This design choice prioritizes internal validity for detecting strategic divergence over proportional representation of the total discursive space.

3.3. Framing Analysis

The coding system followed Van Gorp's (2010) two-stage inductive-deductive method. In the first stage, we conducted open coding of 50 randomly selected videos (25 Democratic, 25 Republican). Two coders independently viewed each video in full, recording recurring thematic patterns, rhetorical strategies, and emotional appeals. Through iterative comparison and consensus discussion, the team identified emergent frame elements until thematic saturation was reached. During this preparatory phase, the two coders resolved all discrepancies through iterative discussion until full consensus was achieved, ensuring conceptual alignment before formal independent coding began. In the second stage, these inductively derived categories were cross-referenced with established frame typologies (Entman, 1993; Nisbet, 2009) to produce the final coding scheme, which was then systematically applied to the full sample of 373 videos.

Our coding dimensions encompassed three levels. Form characteristics included video duration, thumbnail type, and title strategy (Berrocal et al., 2014; Fischer et al., 2022). Content characteristics included: political keywords (Fischer et al., 2022; Semetko & Valkenburg, 2000); political stance on a five-point scale from purely Democratic to purely Republican (Yarchi et al., 2024); partisan mockery; issue frame types integrating Iyengar's (1994) and Semetko and Valkenburg's (2000) typologies; stance expression methods; main issues; political symbols as visual framing (Grabe & Bucy, 2009); and personal image. Emotional characteristics drew on discrete emotion theory (Marcus et al., 2000), including dominant emotion, emotional intensity, target orientation (Papacharissi, 2015), content serialization, engagement level (see Appendix A in the Supplementary File), comment polarization, and opinion distribution.

Comment polarization was assessed using a four-level ordinal scale adapted from prior research on online incivility (Coe et al., 2014; Küchler et al., 2023; see Appendix B for detailed coding criteria and representative comment examples). For each video, two trained coders independently evaluated a systematic random sample of 50 comments, assessing three dimensions: (a) emotional tone, ranging from neutral/factual to overtly hostile; (b) language intensity, from policy-focused discourse to personal attacks; and (c) cross-partisan engagement, from substantive dialogue to complete dismissal. Based on holistic assessment of these dimensions, coders assigned one of four levels: none (exclusively rational, policy-focused discussion without partisan markers), mild (occasional partisan expressions while maintaining substantive cross-ideological engagement), moderate (prevalent partisan language with limited but present cross-partisan dialogue), and high (pervasive partisan hostility, personal attacks, and/or categorical dismissal of opposing views).

Two trained coders independently coded all 373 videos. After a calibration phase involving consensus-based trial coding of 30 videos, formal coding achieved high inter-coder reliability, with an average Cohen's Kappa of 0.975 (range: 0.952 to 1.000 across individual variables; see Appendix C for reliability scores by variable).

3.4. LDA Topic Modeling Analysis

All user comments from the 373 sample videos were collected (n = 795,356). Following standard preprocessing for LDA (Maier et al., 2018), non-English comments, bots, duplicates, and emoji-only comments were removed. Text cleaning included lowercasing, removal of URLs and special characters, tokenization, and application of both standard and custom stop word lists (Schofield et al., 2017). Lemmatization and n-gram techniques were used to preserve the semantic integrity of political terms. The final preprocessed corpus contained 371,124 comments for analysis. Our analysis was limited to publicly available comments and thus excluded deleted or moderated content. The direction of potential bias from this missing content is indeterminate, as including such material could have either strengthened or weakened the observed patterns. This limitation should be considered when interpreting the results. YouTube commenters represent a self-selected subset of the broader audience. Prior research shows that only a declining share of online users participate in comments and that commenters differ systematically from non-commenters (Kalogeropoulos et al., 2017; Newman et al., 2023). Accordingly, the polarization patterns identified should be interpreted as reflecting active commenters' discourse rather than overall audience attitudes.

The LDA model was implemented with Python's Gensim library. The optimal number of topics (K = 8) was determined by evaluating topic coherence and perplexity scores (Blei et al., 2003; Mimno et al., 2011). Hyperparameters were set to $\alpha = 0.15$ and $\beta = 0.05$ to produce concentrated, interpretable topics (Griffiths & Steyvers, 2004).

Topic validity was assessed through a threefold approach evaluating internal semantic coherence, external distinctiveness between topics, and theoretical relevance to established concepts in political communication (Nicholls & Culpepper, 2021). Topic stability was confirmed through bootstrap sampling (500 iterations). Two authors independently reviewed the top 100 high-probability comments per topic and, after three rounds of discussion, assigned the following labels: Topic 1 "Trump truth controversy," Topic 2 "election mobilization and outcomes," Topic 3 "religious moral conflicts," Topic 4 "economic security and extremism accusations," Topic 5 "racial identity politics," Topic 6 "media narratives and personal attacks," Topic 7 "education and generational divides," and Topic 8 "controversial policies and conspiracy theories."

4. Research Findings

4.1. Descriptive Analysis: Strategic Divergence in Partisan Communication and Comment Polarization

The results of the framing analysis address RQ1.

The temporal distribution data (Figure 1) reveal distinctly different content deployment strategies employed by influencers from the two parties. Democrats present a relatively dispersed but clearly nodal publication pattern, reaching peak value in the second week of August (20 videos), with secondary peaks forming in the fourth week of August (18 videos) and the first week of October (19 videos). This multi-peak distribution highly correlates with key event timing, such as the Democratic National Convention and vice-presidential candidate announcement. Republicans demonstrate a more uniform but equally strategic distribution pattern, forming relatively gentle peaks in the third week of August, third week of September, and fourth week of October (approximately 15–16 videos), corresponding respectively to the post-Republican Convention, presidential debate period, and the election sprint phase, embodying a "steady advancement" communication strategy.

Democrats' multi-peak distribution aligns with key political events, reflecting a concentrated effort at critical moments, while Republicans' steadier output pattern suggests a continuous engagement strategy. Both parties' publication frequency drops sharply after election day, confirming that influencer activity is fundamentally election-driven (Tran et al., 2022).

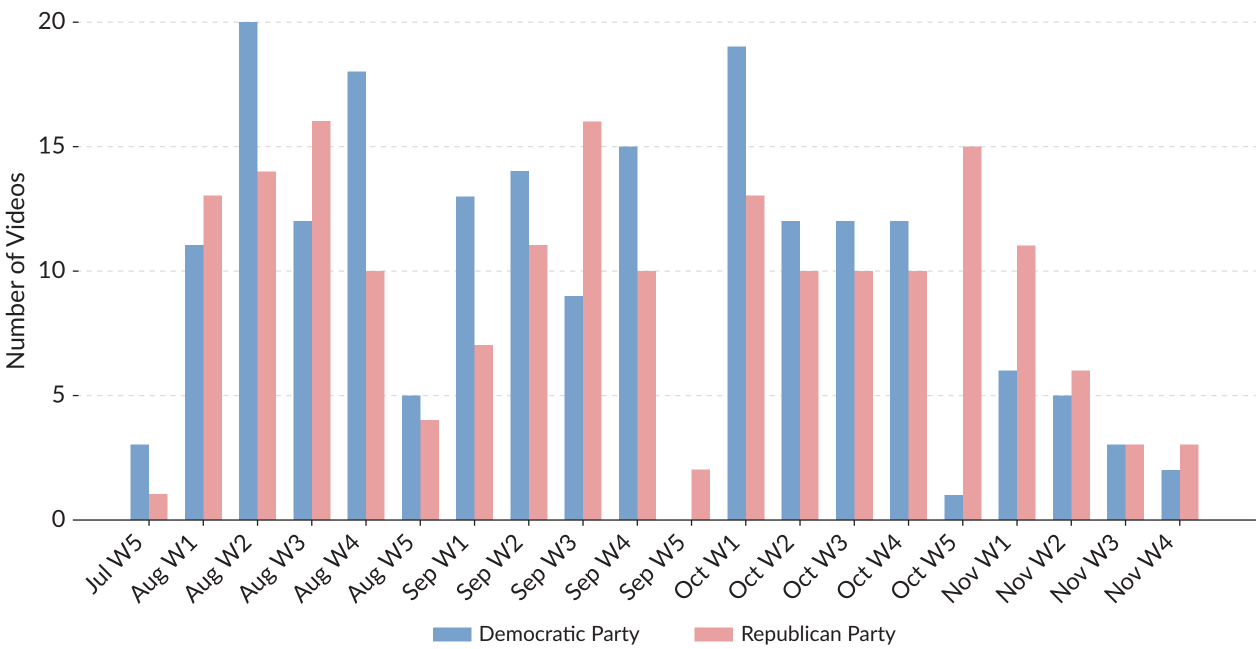

Figure 1. Weekly distribution of content published by Democratic and Republican YouTube political influencers.

The results of the framing analysis (Table 1) reveal divergent framing strategies between the two parties. Compared with Republican influencers, Democratic influencers construct a distinct cognitive architecture by simultaneously emphasizing crisis frames (Democrats: 26% vs. Republicans: 9.4%) and moral frames (Democrats: 28.1% vs. Republicans: 11.6%). This strategy effectively elevates political choices to the level of value-based choices, thereby framing policy disputes as moral conflicts. Compared with Democratic influencers, Republican influencers adopt a markedly different logic, combining a dominant use of opportunity frames (Republicans: 56.4% vs. Democrats: 40.1%) with a pronounced application of explanatory frames (Republicans: 22.7% vs. Democrats: 5.2%). This combination culminates in an "education–persuasion" model. Republican influencers' more frequent use of extra-long videos (Republicans:

21% vs. Democrats: 10.9%) provides greater content capacity to support their primary goal of opinion persuasion (Republicans: 56.4% vs. Democrats: 33.9%).

These framing differences are mirrored in the emotional tenor of the content. Democratic influencers more commonly employ frames of fear and worry (Democrats: 19.3% vs. Republicans: 6.1%), while Republican influencers more frequently leverage frames of hope and pride (Republicans: 23.2% vs. Democrats: 17.7%). Both parties also exhibit high levels of partisan mockery (Republicans: 83.4% vs. Democrats: 76%) and use satirical criticism as a primary mode of stance expression (Republicans: 42% vs. Democrats: 39.1%). This consistent use of confrontational and dismissive communication appears to lay the groundwork for the exacerbation of political polarization.

Table 1. Framing analysis coding categories and results (see Appendix D for detailed category descriptions).

Coding Category	Subcategory	Democratic Influencers (*n*)	Democratic Influencers (%)	Republican Influencers (*n*)	Republican Influencers (%)
Video Duration	Short (<5min)	3	1.6	9	5
	Medium (5–14min)	102	53.1	80	44.2
	Long (15–44min)	66	34.4	54	29.8
	Extra-long (≥45 min)	21	10.9	38	21
Thumbnail Type	Political figure close-up	107	55.7	124	68.5
	Text and figure combination	53	27.6	55	30.4
	Non-political figure close-up	28	14.6	0	0
	Others	4	2.1	2	1.1
Title Strategy	Neutral description	17	8.9	16	8.8
	Emotional inducement	16	8.3	9	5
	Click-bait	143	74.5	147	81.2
	Question-oriented	16	8.3	9	5
Political Keywords	Figures	87	45.3	95	52.5
	Events	70	36.5	55	30.4
	Policies	8	4.2	12	6.6
	Comprehensive topics	24	12.5	16	8.8
	Others	3	1.6	3	1.7
Political Stance	Pure Democratic	133	69.3	0	0
	Democratic-leaning	41	21.4	0	0
	Neutral	13	6.8	0	0
	Republican-leaning	5	2.6	41	22.7
	Pure Republican	0	0	140	77.3
Partisan Mockery	Absent	46	24	30	16.6
	Present	146	76	151	83.4

Table 1. (Cont.) Framing analysis coding categories and results (see Appendix D for detailed category descriptions).

Coding Category	Subcategory	Democratic Influencers (*n*)	Democratic Influencers (%)	Republican Influencers (*n*)	Republican Influencers (%)
Issue Frame Type	Crisis frame	50	26	17	9.4
	Opportunity frame	77	40.1	102	56.4
	Moral frame	54	28.1	21	11.6
	Explanatory frame	10	5.2	41	22.7
	Economic frame	1	0.5	0	0
Stance Expression Method	Direct expression	91	47.4	65	35.9
	Implicit suggestion	4	2.1	17	9.4
	Satirical criticism	75	39.1	76	42
	Education and explanation	22	11.5	23	12.7
Main Issues	Economy	6	3.1	5	2.8
	Campaign events	128	66.7	115	63.5
	Culture	14	7.3	9	5
	Foreign affairs	2	1	2	1.1
	Institutional	21	10.9	22	12.2
	Others	21	10.9	28	15.5
Political Symbols	American flag	64	33.3	50	27.6
	Party symbols	20	10.4	20	11
	None	108	56.3	111	61.3
Personal Image	Formal professional	83	43.2	81	44.8
	Casual	81	42.2	39	21.5
	Personalized	10	5.2	61	33.7
	Authoritative	18	9.4	0	0
Dominant Emotion	Anger	30	15.6	26	14.4
	Fear and worry	37	19.3	11	6.1
	Hope and pride	34	17.7	42	23.2
	Humor and mockery	56	29.2	56	30.9
	Rationality	35	18.2	46	25.4
Emotional Intensity	Low intensity	28	14.6	22	12.2
	Medium intensity	73	38	82	45.3
	High intensity	91	47.4	77	42.5
Target Orientation	Group identity	58	30.2	40	22.1
	Call to action	26	13.5	9	5
	Opinion persuasion	65	33.9	102	56.4
	Emotional catharsis	43	22.4	30	16.6
Content Serialization	Regular series	150	78.1	150	82.9
	Standalone videos	42	21.9	31	17.1

Table 1. (Cont.) Framing analysis coding categories and results (see Appendix D for detailed category descriptions).

Coding Category	Subcategory	Democratic Influencers (*n*)	Democratic Influencers (%)	Republican Influencers (*n*)	Republican Influencers (%)
Engagement Level (Views/ Comments)	Low engagement	19	9.9	13	7.2
	Medium engagement	72	37.5	39	21.5
	High engagement	101	52.6	129	71.3
Comment Polarization	None	0	0	3	1.7
	Mild polarization	17	8.9	25	13.8
	Moderate polarization	80	41.7	59	32.6
	High polarization	95	49.5	94	51.9
Opinion Distribution	One-sided	77	40.1	94	51.9
	Supportive	80	41.7	79	43.6
	Divided	33	17.2	7	3.9
	Opposed	2	1	1	0.6

LDA topic modeling of 371,124 comments yielded the following results to address RQ2.

Through LDA topic modeling analysis (Table 2), eight distinct topics were ultimately identified, which can be grouped into three core dimensions by semantic relevance: (a) candidate and partisan identity polarization, covering Topic 1 ("Trump truth controversy," 20.3%), Topic 2 ("election mobilization and outcomes," 17.2%), and Topic 6 ("media narratives and personal attacks," 18.9%); (b) values and cultural identity polarization, involving Topic 3 ("religious moral conflicts," 6.3%), Topic 5 ("racial identity politics," 10.9%), and Topic 7 ("education and generational divides," 9.4%); (c) policy issues and extremist labeling, containing Topic 4 ("economic security and extremism accusations," 11.6%) and Topic 8 ("controversial policies and conspiracy theories," 5.4%).

Table 2. LDA analysis results and category identification.

Topic No.	Sample Count	Proportion	Label	Representative Words	Category Identification
1	75,445	0.20329	Trump truth controversy	trump, lie, harris, campaign, truth, republican, democrat, love, sad, racist, party, crazy, hope, walz, vance	Candidate & partisan identity polarization
2	63,710	0.17167	Election mobilization and outcomes	vote, trump, democrat, country, win, america, president, republican, harris, party, lose, hope, fear, democracy, moral	Candidate & partisan identity polarization
3	23,415	0.06309	Religious moral conflicts	church, abortion, child, love, kill, hope, evil, bless, happy, truth, family, heart, america, jewish, anti	Values & cultural identity polarization

Table 2. (Cont.) LDA analysis results and category identification.

Topic No.	Sample Count	Proportion	Label	Representative Words	Category Identification
4	43,016	0.1159	Economic security and extremism accusations	money, fascist, country, government, america, free, trump, border, business, military, war, criminal, law, tax, economy	Policy issues & extremist labeling
5	40,335	0.10868	Racial identity politics	family, black, white, woman, house, price, asian, trump, harris, child, economy, obama, racist, race, culture	Values & cultural identity polarization
6	70,222	0.18921	Media narratives and personal attacks	trump, debate, stupid, media, harris, president, hope, criminal, lose, truth, jail, law, biden, laugh, musk	Candidate & partisan identity polarization
7	34,709	0.09363	Education and generational divides	child, school, truth, trump, experience, woman, grade, relationship, class, argue, family, smart, learn, change, kill	Values & cultural identity polarization
8	20,225	0.05449	Controversial policies and conspiracy theories	gun, fight, border, pet, immigration, vaccine, construction, hasan, hand, check, direction, garbage, kill, mark, car, police, violence	Policy issues & extremist labeling

According to the topic distribution analysis, candidate-related topics dominate. The top three high-frequency topics, "Trump truth controversy," "media narratives and personal attacks," and "election mobilization and outcomes," collectively account for 56.4% of the total, indicating that online discussions during the 2024 election were highly concentrated around candidates' personal characteristics and partisan opposition rather than specific policy issues (Pereira et al., 2023). This personalized political discussion model reflects key characteristics of current American political discourse. While this distribution is consistent with the personalization of political discourse, we note that a predominant focus on political competition does not inherently indicate polarization. Political candidates and partisan dynamics can be discussed without fostering intergroup hostility. The personalization pattern becomes polarizing, specifically when accompanied by affective hostility and out-group derogation, as the high levels of personal attacks (Topic 6: 18.9%) and comment polarization documented in Section 4.2 confirm.

In the vocabulary distribution, several features stand out: First, in Topic 3, religion-related vocabulary shows concentrated occurrence ("church," "abortion," "bless"), indicating religion's core role in political polarization phenomena. Second, in Topic 5, racial marker words appear with high frequency and co-occurrence ("black," "white," "racist," "race"), showing racial identity's significant importance in political discussion. Third, in Topic 4, extremist language ("fascist," "criminal," "border") coexists with economic issue vocabulary ("economy," "business," "tax"), indicating policy discussions have been infiltrated by extremist language (Calice et al., 2023).

To examine the analytical link between influencer framing strategies and comment discourse, we cross-tabulated the manually coded video frames with the LDA topic distribution (see Appendix E) in their associated comment sections. Several patterns merit attention. First, videos coded with moral frames were associated with elevated proportions of Topic 6 ("media narratives and personal attacks") across both parties (Democratic: 23.7%, Republican: 23.8%), compared with other frame types, suggesting that moral framing may channel comment discourse toward personalized attacks. Second, among Republican influencer videos, those employing explanatory frames showed a higher proportion of Topic 7 ("education and generational divides": 11.5%) than videos with other frame types, consistent with the education-persuasion framing model identified in the content analysis. Third, videos with humor as the dominant emotion were associated with elevated proportions of Topic 6 across both parties (Democratic: 26.4%, Republican: 22.2%), confirming the link between satirical content and personalized political discourse in the comment sections. These cross-modal patterns indicate that the thematic structure of comment discourse is not independent of influencer framing strategies but is systematically associated with them, thereby demonstrating the integrative analytical value of combining framing analysis with topic modeling.

In summary, the framing analysis and LDA results document systematic strategic divergence alongside pervasive affective polarization patterns, as discussed further in Section 5.

4.2. The Triple Dimensions of Polarization: Content Strategy, Emotional Mobilization, and Platform Dynamics

Building on the descriptive patterns identified above, this section further examines the temporal dynamics underlying the strategic divergence in RQ1 and the polarization patterns in RQ2.

First, in the dimension of content strategy (Figure 2), the temporal evolution of frame types reveals a dynamic process of content polarization. Democratic influencers' use of crisis frames was most prominent during the early campaign period (late July to mid-August), exceeding 70%, before gradually decreasing as the election approached. This pattern, consistent with the "critical point narrative" suggested by prior research, may evoke a sense of urgency among audiences. In contrast, Republican influencers' opportunity frames consistently remained at high levels, surpassing 50% throughout. This consistency may be interpreted as conveying a sense of certainty, which could facilitate audience identification (Cole et al., 2025; Iyengar et al., 2019).

Second, temporal analysis of emotional mobilization reveals distinct mechanisms of emotional polarization. Democratic influencers' emotional strategy shows distinct phase-specific characteristics: humor and hope were both prominent in the early period (July–August), rationality in the middle phase (September), and fear and worry in the late stage (October). By comparison, Republican influencers' emotional tone maintained greater consistency with rationality being the most stable emotional characteristic throughout the campaign period, while hope and pride surged in the post-election weeks (November).

Third, comment polarization data suggest that platform architecture may be implicated in polarization dynamics (Brown et al., 2022). Although the two parties employ distinct content and emotional strategies, both produce similarly high levels of polarization (approximately 50%), suggesting a structural alignment in the platform architecture itself. Republican videos exhibit clear characteristics of "homogeneous polarization" (one-sided support was 51.9% while opinion division was only 3.9%), which aligns with their

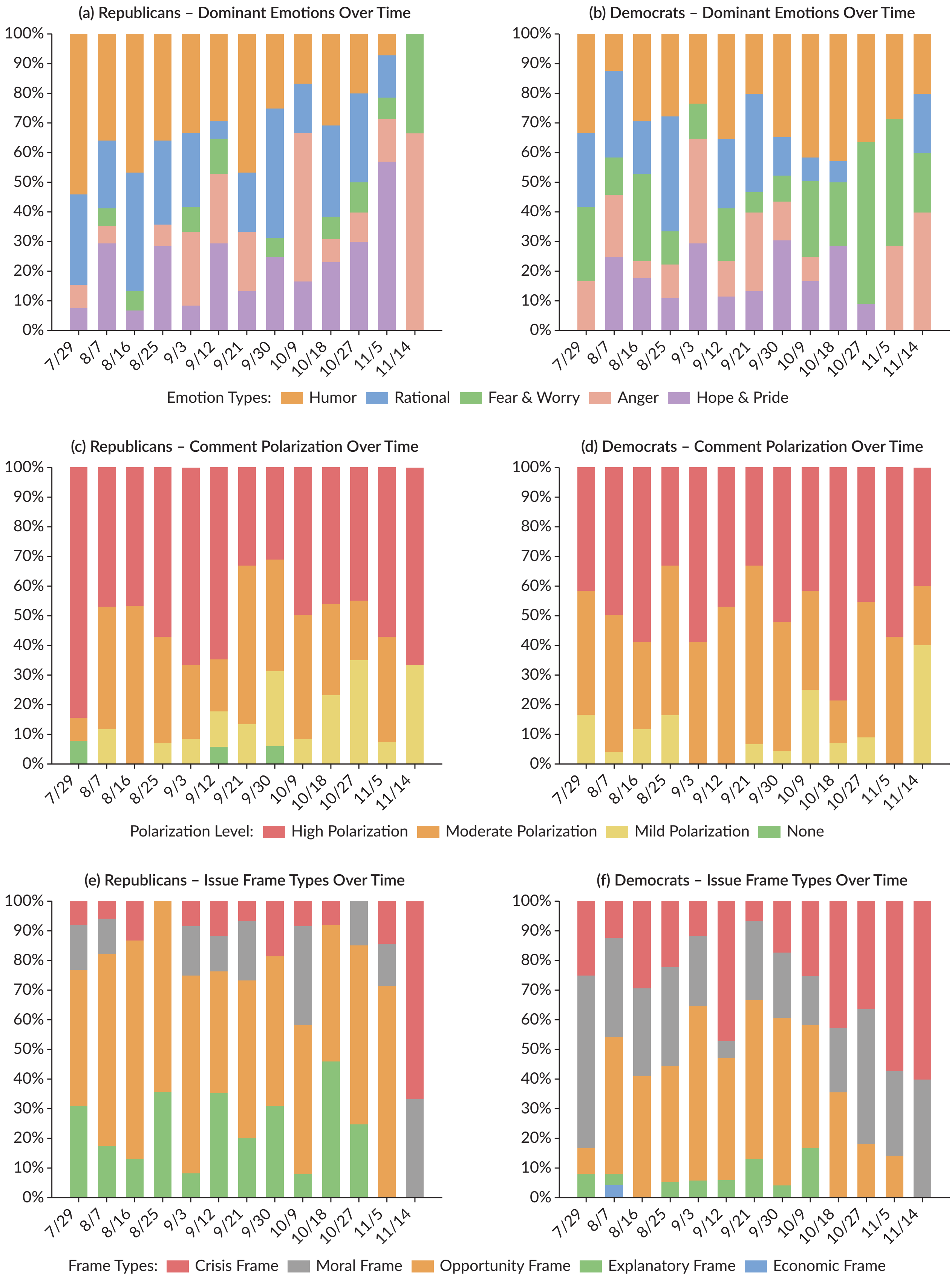

Figure 2. Temporal charts of dominant emotions, polarization degree, and frame quantity in content published by Democratic and Republican YouTube political influencers.

33.7% prevalence of personalized image usage. This pattern is consistent with prior theoretical accounts suggesting that personal charisma-based influence may foster defensive group identity dynamics (Schramm et al., 2024). Although Democratic videos show a higher degree of opinion division (17.2%), this diversity may mask deeper splits, where different subgroups draw entirely different conclusions from the same content, forming a pattern of "polarization within polarization."

Engagement data yield another insight: Compared with Democratic influencers, Republican videos show higher engagement rates (Republicans: 71.3% > Democrats: 52.6%), yet this does not translate into proportionally higher polarization, suggesting the existence of a "ceiling effect" in polarization dynamics. That is, when user groups are already highly polarized, further engagement primarily manifests as repeated interaction within homogeneous groups rather than producing new forms of polarization. This pattern is consistent with prior research suggesting that platform dynamics may interact with pre-existing polarization tendencies (Chen et al., 2023).

4.3. YouTube Polarization Risk Assessment Scale: From Empirical Findings to Theoretical Construction

We proposed the YouTube polarization risk assessment (YPRA) scale to address RQ3. Building on the framing analysis and LDA findings reported above, the YPRA scale integrates five content-level indicators into a weighted model designed to assess the polarization risk of individual videos. Its development proceeds from a core premise grounded in the preceding analyses: Comment polarization arises from the interaction of multiple content and emotional factors, and thus no single dimension can fully account for its complexity (Table 3).

Table 3. YPRA scale indicators and scoring.

Core Indicator	Category and Scores
Political Stance Strength (35%)	Pure stance: 9 points; Leaning stance: 4 points; Neutral: 1 point
Dominant Emotion (30%)	Humor/Sarcasm: 10 points; Anger: 9 points; Hope & Pride: 5 points; Fear & Worry: 4 points; Rationality: 3 points
Engagement Level (20%)	High engagement: 8 points; Medium engagement: 5 points; Low engagement: 2 points
Emotional Intensity (10%)	High intensity: 10 points; Medium intensity: 6 points; Low intensity: 2 points
Partisan Mockery (5%)	Present: 8 points; Absent: 2 points
Risk Thresholds	Low Risk: Weighted Score <4; Medium Risk: 4–6; High Risk: >6

To empirically ground the scale weights rather than relying solely on theoretical assumptions, we conducted an ordinary least squares regression analysis (see Appendix F, Tables F1–F3) with comment polarization as the dependent variable and five content-level indicators as independent predictors ($N = 373$). The model achieved an R^2 of 0.224 ($F = 13.13$, $p < 0.001$), indicating that the five indicators collectively explain approximately 22.4% of the variance in comment polarization. While modest, this level of explanatory power is consistent with the inherent complexity of modeling online political behavior, where numerous contextual and individual-level factors beyond content characteristics influence polarization dynamics.

The regression analysis revealed three statistically significant predictors. Political Stance Strength emerged as the strongest predictor ($\beta = 0.355$, $p < 0.001$), confirming that clearly partisan content is the most robust correlate of comment polarization. Dominant Emotion showed a notable pattern: Humor/Sarcasm ($\beta = 0.350$, $p = 0.001$) exhibited a slightly stronger association with comment polarization than Anger ($\beta = 0.314$, $p = 0.012$). Engagement Level was also significant ($\beta = 0.198$, $p = 0.001$), suggesting that high-engagement environments are associated with more polarized comment discourse. Emotional Intensity was marginally significant ($\beta = 0.107$, $p = 0.058$), while Partisan Mockery did not reach statistical significance ($\beta = 0.116$, $p = 0.182$). Fear ($\beta = 0.044$, $p = 0.727$) and Hope ($\beta = 0.089$, $p = 0.418$) were not significant predictors of comment polarization.

Based on the normalized regression coefficients, the YPRA scale weights were empirically calibrated as follows: political stance strength (35%), dominant emotion (30%, with humor/sarcasm and anger assigned the highest risk scores), engagement level (20%), emotional intensity (10%), and partisan mockery (5%). This data-driven calibration replaced the initial literature-based weighting scheme, grounding the scale in the empirical patterns observed in this sample.

5. Discussion

This study examines whether YouTube political influencers function as architects of affective polarization or merely as mirrors reflecting pre-existing partisan divisions.

Addressing RQ1, the framing analysis reveals divergent strategies between Democratic and Republican influencers: the former relied on a moral–crisis dual construction, whereas the latter predominantly employed an opportunity–explanation model. This divergence challenges the assumption that platform environments necessarily homogenize partisan content strategies (Haroon et al., 2023), yet the observation that both camps produce similarly high polarization levels (approximately 50%) illustrates a paradox consistent with Van Dijck et al.'s (2018) analysis of platform societies: strategic diversity coexisting with convergent polarization outcomes.

Addressing RQ2, LDA topic modeling identified eight distinct thematic clusters, more than half of which (56.4%) centered on candidate personality rather than substantive policy debates. This pattern is consistent with the theoretical prediction that affective partisanship can drive political divergence even in the absence of prior ideological disagreement (Diermeier & Li, 2023): When comment discourse gravitates toward personal attacks rather than policy engagement, it suggests that emotional hostility may function as a contributing factor in—rather than merely a consequence of—political division.

Addressing RQ3, the empirically calibrated YPRA scale demonstrates that Political Stance Strength, Humor/Sarcasm, and Anger emerged as the three strongest predictors of comment polarization, with Political Stance and Dominant Emotion together accounting for 65% of the total scale weight. The finding that Humor/Sarcasm showed a slightly stronger statistical association with comment polarization than Anger complicates conventional accounts of online hostility that foreground overt anger. This result extends affective intelligence theory (Marcus et al., 2000) while suggesting a more compressed pathway to polarization than previous accounts of gradual radicalization: A single high-intensity video is associated with polarization levels that might otherwise require sustained exposure.

6. Conclusion

The pervasive presence of partisan mockery across both orientations (Democrats: 76%; Republicans: 83.4%) aligns with the predictions of social identity theory (Tajfel & Turner, 2001). Mockery appears to function not merely as a rhetorical device but as what we might term “affective infrastructure,” potentially reinforcing the emotional basis of partisan identity. This sheds light on the mutually reinforcing cycle between “perceived polarization” and “actual polarization” (Yarchi et al., 2024): By foregrounding personality over policy, influencers provide audiences with abundant signals for affective evaluation but limited material for ideological assessment. The consistent deployment of politicized visual imagery across both orientations further confirms that visual framing operates as a parallel persuasive channel, reinforcing verbal frames (Geise & Baden, 2015).

The regression finding that humor/sarcasm surpasses anger as a predictor of comment polarization is consistent with recent work on the political functions of humor (Beck & Spencer, 2025). Sarcasm may operate through implied superiority and collective derision, establishing exclusionary community boundaries that are difficult to challenge precisely because they are framed as entertainment rather than hostility. This mechanism may explain why humor-dominant videos showed the highest proportions of personalized attacks in comment discourse.

Theoretically, these findings point to a systematic distortion of Habermasian ideals of rational–critical debate. When approximately half of all videos exhibit high comment polarization (50.7% overall; Democrats: 49.5%, Republicans: 51.9%), what emerges is not a marketplace of ideas but an “echo-chamber resonance.” The “ceiling effect” we observe, where Republican videos show higher engagement yet not proportionally higher polarization, suggests a modification to the law of group polarization (Sunstein, 2002): Within platform architectures already saturated with high-intensity content, additional emotional intensity yields diminishing returns. Prior research has described how platform features such as recommendation systems can shape content visibility (Brown et al., 2022; Haroon et al., 2023). While the present study did not directly examine these processes, the observed association between engagement levels and comment polarization raises questions about the role of platform architecture that warrant investigation in future research.

In summary, the 2024 US election on YouTube was characterized by a confluence of entertainment-driven expression, emotional intensification, and entrenched partisan divisions. Within this platform ecology, characterized by attention-driven dynamics and intensive partisan communication, high levels of comment polarization appear as a persistent feature across both influencer orientations. The shift from the “post-truth” dynamics of 2016 through to the “discursive struggle over truth” in 2020, and finally to the “polarization ceiling” of 2024, suggests a steady erosion of deliberative norms. Emotion and antagonism increasingly displace rational argument in digital electoral communication. This transformation of electoral communication prompts a critical question: Is this trajectory compatible with democratic health?

These findings offer two implications for platform governance. First, risk assessment tools such as the YPRA scale can guide algorithm adjustments to reduce the visibility of highly polarized content. Second, enforcing stricter transparency for political influencer sponsorships could strengthen accountability in digital political communication.

This study has several limitations. First, while the sample of 40 major English-language influencers is representative, it may not fully capture niche creators, and videos deleted before or during sampling were not included. Additionally, the balanced sampling design (20 Democratic and 20 Republican influencers) may underrepresent the overall conservative dominance in YouTube's political ecosystem; future research employing proportional sampling could complement these findings. Second, as a platform-specific study of YouTube, the generalizability of the findings to other social media environments requires further validation. Third, although the research establishes robust associations between communication strategies and polarization, inferring causality necessitates future experimental or longitudinal research designs. Furthermore, the weighting scheme of the YPRA scale is primarily derived from empirical regression analysis within this specific election cycle. Alternative weighting configurations were not systematically tested, representing a limitation that future studies should address through robustness checks across different electoral contexts and platforms.

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Conflict of Interests

The authors declare no conflict of interest.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request, subject to ethical and privacy restrictions.

LLMs Disclosure

No large language models were used in the research or writing of this article.

Supplementary Material

Supplementary material for this article is available online in the format provided by the author (unedited).

References

Beck, D., & Spencer, A. (2025). (Un)funny against all odds: The changing landscape of humour in politics. *Alternatives*, *50*(1), 3–17. https://doi.org/10.1177/03043754241290911

Berrocal, S., Campos-Domínguez, E., & Redondo, M. (2014). Media prosumers in political communication: Politainment on YouTube. *Comunicar*, *22*(43), 65–72. https://doi.org/10.3916/C43-2014-06

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent Dirichlet allocation. *Journal of Machine Learning Research*, *3*, 993–1022. http://www.jmlr.org/papers/v3/blei03a.html

Brown, M. A., Bisbee, J., Lai, A., Bonneau, R., Nagler, J., & Tucker, J. A. (2022). *Echo chambers, rabbit holes, and algorithmic bias: How YouTube recommends content to real users*. SSRN. https://doi.org/10.2139/ssrn.4114905

Bucher, T., & Helmond, A. (2018). The affordances of social media platforms. In J. Burgess, A. Marwick, & T. Poell (Eds.), *The Sage handbook of social media* (pp. 233–253). Sage. https://doi.org/10.4135/9781473984066.n14

Calice, M. N., Bao, L., Freiling, I., Howell, E., Xenos, M. A., Yang, S., Brossard, D., Newman, T. P., & Scheufele, D. A. (2023). Polarized platforms? How partisanship shapes perceptions of "algorithmic news bias." *New Media & Society*, *25*(11), 2833–2854. https://doi.org/10.1177/14614448211034159

Chen, A. Y., Nyhan, B., Reifler, J., Robertson, R. E., & Wilson, C. (2023). Subscriptions and external links help drive resentful users to alternative and extremist YouTube channels. *Science Advances*, *9*(35), Article eadd8080. https://doi.org/10.1126/sciadv.add8080

Coe, K., Kenski, K., & Rains, S. A. (2014). Online and uncivil? Patterns and determinants of incivility in newspaper website comments. *Journal of Communication*, *64*(4), 658–679. https://doi.org/10.1111/jcom.12104

Cohen, J., & Holbert, R. L. (2021). Assessing the predictive value of parasocial relationship intensity in a political context. *Communication Research*, *48*(4), 501–526. https://doi.org/10.1177/0093650218759446

Cole, J. C., Gillis, A. J., van der Linden, S., Cohen, M. A., & Vandenbergh, M. P. (2025). Social psychological perspectives on political polarization: Insights and implications for climate change. *Perspectives on Psychological Science*, *20*(1), 115–141. https://doi.org/10.1177/17456916231186409

Dan, V. (2017). *Integrative framing analysis: Framing health through words and visuals*. Routledge. https://doi.org/10.4324/9781315171456

Diermeier, D., & Li, C. (2023). Dynamics of polarization: Affective partisanship and policy divergence. *British Journal of Political Science*, *53*(3), 980–996. https://doi.org/10.1017/S0007123422000540

Druckman, J. N., Klar, S., Krupnikov, Y., Levendusky, M., & Ryan, J. B. (2022). (Mis)estimating affective polarization. *The Journal of Politics*, *84*(2), 1106–1117. https://doi.org/10.1086/715603

Entman, R. M. (1993). Framing: Toward clarification of a fractured paradigm. *Journal of Communication*, *43*(4), 51–58. https://doi.org/10.1111/j.1460-2466.1993.tb01304.x

Evans, S. K., Pearce, K. E., Vitak, J., & Treem, J. W. (2017). Explicating affordances: A conceptual framework for understanding affordances in communication research. *Journal of Computer-Mediated Communication*, *22*(1), 35–52. https://doi.org/10.1111/jcc4.12180

Fischer, T. S., Kolo, C., & Mothes, C. (2022). Political influencers on YouTube: Business strategies and content characteristics. *Media and Communication*, *10*(1), 259–271. https://doi.org/10.17645/mac.v10i1.4767

Freelon, D., Marwick, A., & Kreiss, D. (2020). False equivalencies: Online activism from left to right. *Science*, *369*(6508), 1197–1201. https://doi.org/10.1126/science.abb2428

Geise, S., & Baden, C. (2015). Putting the image back into the frame: Modeling the linkage between visual communication and frame-processing theory. *Communication Theory*, *25*(1), 46–69. https://doi.org/10.1111/comt.12048

Gillespie, T. (2018). *Custodians of the internet: Platforms, content moderation, and the hidden decisions that shape social media*. Yale University Press. https://doi.org/10.12987/9780300235029

Grabe, M. E., & Bucy, E. P. (2009). *Image bite politics: News and the visual framing of elections*. Oxford University Press. https://doi.org/10.1093/acprof:oso/9780195372076.001.0001

Griffiths, T. L., & Steyvers, M. (2004). Finding scientific topics. *Proceedings of the National Academy of Sciences*, 101(Suppl. 1), 5228–5235. https://doi.org/10.1073/pnas.0307752101

Harff, D., Stehr, P., & Schmuck, D. (2025). Revisiting opinion leadership in the digital realm: Social media influencers as proximal mass opinion leaders. *New Media & Society*. Advance online publication. https://doi.org/10.1177/14614448251336441

Haroon, M., Wojcieszak, M., Chhabra, A., Liu, X., Mohapatra, P., & Shafiq, Z. (2023). Auditing YouTube's recommendation system for ideologically congenial, extreme, and problematic recommendations. *Proceedings of the National Academy of Sciences*, *120*(50), Article e2213020120. https://doi.org/10.1073/pnas.2213020120

Hosseinmardi, H., Ghasemian, A., Clauset, A., Mobius, M., Rothschild, D. M., & Watts, D. J. (2021). Examining the consumption of radical content on YouTube. *Proceedings of the National Academy of Sciences*, *118*(32), Article e2101967118. https://doi.org/10.1073/pnas.2101967118

Iyengar, S. (1994). *Is anyone responsible?: How television frames political issues*. University of Chicago Press.

Iyengar, S., Lelkes, Y., Levendusky, M., Malhotra, N., & Westwood, S. J. (2019). The origins and consequences of affective polarization in the United States. *Annual Review of Political Science*, 22, 129–146. https://doi.org/10.1146/annurev-polisci-051117-073034

Iyengar, S., & Westwood, S. J. (2015). Fear and loathing across party lines: New evidence on group polarization. *American Journal of Political Science*, *59*(3), 690–707. https://doi.org/10.1111/ajps.12152

Kalogeropoulos, A., Negredo, S., Picone, I., & Nielsen, R. K. (2017). Who shares and comments on news? A cross-national comparative analysis of online and social media participation. *Social Media + Society*, *3*(4). https://doi.org/10.1177/2056305117735754

Kim, H., Jang, S. M., Kim, S.-H., & Wan, A. (2018). Evaluating sampling methods for content analysis of Twitter data. *Social Media + Society*, *4*(2). https://doi.org/10.1177/2056305118772836

Küchler, C., Stoll, A., Ziegele, M., & Naab, T. K. (2023). Gender-related differences in online comment sections: Findings from a large-scale content analysis of commenting behavior. *Social Science Computer Review*, *41*(3), 728–747. https://doi.org/10.1177/08944393211052042

Maier, D., Waldherr, A., Miltner, P., Wiedemann, G., Niekler, A., Keinert, A., Pfetsch, B., Heyer, G., Reber, U., Häussler, T., Schmid-Petri, H., & Adam, S. (2018). Applying LDA topic modeling in communication research: Toward a valid and reliable methodology. *Communication Methods and Measures*, 12(2/3), 93–118. https://doi.org/10.1080/19312458.2018.1430754

Mall, R., Nagpal, M., Salminen, J., Almerekhi, H., Jung, S. G., & Jansen, B. J. (2024). Politics on YouTube: Detecting online group polarization based on news videos' comments. *Sage Open*, *14*(2). https://doi.org/10.1177/21582440241256438

Marcus, G. E., Neuman, W. R., & MacKuen, M. (2000). *Affective intelligence and political judgment*. University of Chicago Press.

McLuhan, M. (1994). *Understanding media: The extensions of man*. MIT Press.

Mimno, D., Wallach, H., Talley, E., Leenders, M., & McCallum, A. (2011). Optimizing semantic coherence in topic models. In R. Barzilay & M. Johnson (Eds.), *Proceedings of the 2011 Conference on Empirical Methods in Natural Language Processing* (pp. 262–272). Association for Computational Linguistics. https://aclanthology.org/D11-1024

Müller, M. G., & Geise, S. (2015). *Grundlagen der Visuellen Kommunikation: Theorieansätze und Analysemethoden* (2nd ed.). UVK Verlag. https://doi.org/10.36198/9783838524146

Newman, N., Fletcher, R., Eddy, K., Robertson, C. T., & Nielsen, R. K. (2023). *Reuters Institute digital news report 2023*. Reuters Institute for the Study of Journalism. https://reutersinstitute.politics.ox.ac.uk/digital-news-report/2023

Nicholls, T., & Culpepper, P. D. (2021). Computational identification of media frames: Strengths, weaknesses, and opportunities. *Political Communication*, 38(1/2), 159–181. https://doi.org/10.1080/10584609.2020.1812777

Nieland, J.-U. (2008). Politainment. In W. Donsbach (Ed.), *The international encyclopedia of communication*. Wiley. https://doi.org/10.1002/9781405186407.wbiecp047

Nisbet, M. C. (2009). Communicating climate change: Why frames matter for public engagement. *Environment: Science and Policy for Sustainable Development*, *51*(2), 12–23. https://doi.org/10.3200/ENVT.51.2.12-23

Papacharissi, Z. (2015). *Affective publics: Sentiment, technology, and politics*. Oxford University Press. https://doi.org/10.1093/acprof:oso/9780199999736.001.0001

Pereira, A., Harris, E., & Van Bavel, J. J. (2023). Identity concerns drive belief: The impact of partisan identity on the belief and dissemination of true and false news. *Group Processes & Intergroup Relations*, *26*(1), 24–47. https://doi.org/10.1177/13684302211030004

Riedl, M. J., Lukito, J., & Woolley, S. C. (2023). Political influencers on social media: An introduction. *Social Media + Society*, *9*(2). https://doi.org/10.1177/20563051231177938

Rodriguez, L., & Dimitrova, D. V. (2011). The levels of visual framing. *Journal of Visual Literacy*, *30*(1), 48–65. https://doi.org/10.1080/23796529.2011.11674684

Rogers, R. (2019). *Doing digital methods*. Sage. https://doi.org/10.4135/9781036231514

Rose, K., & Rohlinger, D. A. (2024). Political influencers and their social media audiences during the 2021 Arizona audit. *Socius*, *10*. https://doi.org/10.1177/23780231241259680

Schneiker, A., Dau, M., Joachim, J., Martin, M., & Lange, H. (2019). How to analyze social media? Assessing the promise of mixed-methods designs for studying the Twitter feeds of PMSCs. *International Studies Perspectives*, *20*(2), 188–200. https://doi.org/10.1093/isp/eky013

Schofield, A., Magnusson, M., & Mimno, D. (2017). Pulling out the stops: Rethinking stopword removal for topic models. In M. Lapata, P. Blunsom, & A. Koller (Eds.), *Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 2, short papers* (pp. 432–436). Association for Computational Linguistics. https://aclanthology.org/E17-2069

Schradie, J. (2019). *The revolution that wasn't: How digital activism favors conservatives*. Harvard University Press.

Schramm, H., Liebers, N., Biniak, L., & Dettmar, F. (2024). Research trends on parasocial interactions and relationships with media characters. A review of 281 English and German-language studies from 2016 to 2020. *Frontiers in Psychology*, *15*, Article 1418564. https://doi.org/10.3389/fpsyg.2024.1418564

Schwemmer, C., & Riedl, M. (2025). From hashtags to ballots: Conceptualizing political influencers and evaluating their impact on election outcomes. *PLoS ONE*, *20*(5), Article e0321592. https://doi.org/10.1371/journal.pone.0321592

Semetko, H. A., & Valkenburg, P. M. (2000). Framing European politics: A content analysis of press and television news. *Journal of Communication*, *50*(2), 93–109. https://doi.org/10.1111/j.1460-2466.2000.tb02843.x

Shevtsov, A., Oikonomidou, M., Antonakaki, D., Pratikakis, P., & Ioannidis, S. (2023). What Tweets and YouTube comments have in common? Sentiment and graph analysis on data related to US elections 2020. *PLoS ONE*, *18*(1), Article e0270542. https://doi.org/10.1371/journal.pone.0270542

Shifman, L. (2014). The cultural logic of photo-based meme genres. *Journal of Visual Culture*, *13*(3), 340–358. https://doi.org/10.1177/1470412914546577

Stocking, G., Wang, L., Lipka, M., Matsa, K. E., Widjaya, R., Tomasik, E., & Liedke, J. (2024). *News influencers on YouTube: Who they are and what they post about*. Pew Research Center. https://www.pewresearch.org/journalism/2024/11/18/news-influencers-on-youtube

Sunstein, C. R. (2002). The law of group polarization. *Journal of Political Philosophy*, *10*(2), 175–195. https://doi.org/10.1111/1467-9760.00148

Tajfel, H., & Turner, J. C. (2001). An integrative theory of intergroup conflict. In M. A. Hogg & D. Abrams (Eds.), *Intergroup relations: Essential readings* (pp. 94–109). Psychology Press.

Tran, G. T., Nguyen, L. V., Jung, J. J., & Han, J. (2022). Understanding political polarization based on user activity: A case study in Korean political YouTube channels. *Sage Open*, *12*(2). https://doi.org/10.1177/21582440221094587

Turcotte, J., York, C., Irving, J., Scholl, R. M., & Pingree, R. J. (2015). News recommendations from social media opinion leaders: Effects on media trust and information seeking. *Journal of Computer-Mediated Communication*, *20*(5), 520–535. https://doi.org/10.1111/jcc4.12127

Van Dijck, J., Poell, T., & de Waal, M. (2018). *The platform society: Public values in a connective world*. Oxford University Press. https://doi.org/10.1093/oso/9780190889760.001.0001

Van Gorp, B. (2010). Strategies to take subjectivity out of framing analysis. In P. D'Angelo & J. Kuypers (Eds.), *Doing news framing analysis* (pp. 84–109). Routledge. https://doi.org/10.4324/9780203864463-11

Walter, D., & Ophir, Y. (2019). News frame analysis: An inductive mixed-method computational approach. *Communication Methods and Measures*, *13*(4), 248–266. https://doi.org/10.1080/19312458.2019.1639145

Yarchi, M., Baden, C., & Kligler-Vilenchik, N. (2024). Political polarization on the digital sphere: A cross-platform, over-time analysis of interactional, positional, and affective polarization on social media. In K. Koc-Michalska, U. Klinger, L. Bennett, & A. Römmele (Eds.), *Dissonant public spheres* (pp. 185–226). Routledge. https://doi.org/10.4324/9781003479598-17

Ylä-Anttila, T., Eranti, V., & Kukkonen, A. (2022). Topic modeling for frame analysis: A study of media debates on climate change in India and USA. *Global Media and Communication*, *18*(1), 91–112. https://doi.org/10.1177/17427665211023984

Yu, X., Haroon, M., Menchen-Trevino, E., & Wojcieszak, M. (2024). Nudging recommendation algorithms increases news consumption and diversity on YouTube. *PNAS Nexus*, *3*(12), Article pgae518. https://doi.org/10.1093/pnasnexus/pgae518

Zakrzewski, C. (2024, October 26). Political groups pay influencers this election, without disclosures. *The Washington Post*. https://www.washingtonpost.com/technology/2024/10/26/social-media-influencers-election-money-campaigns

About the Authors

Xianquan Zeng is a postgraduate student at the School of Literature and Journalism, Hunan Polytechnic University. His research interests include, but are not limited to, political communication, media and society, and intercultural communication.

Jiarun Du is a postgraduate student at the School of Literature and Journalism, Hunan Polytechnic University. His research interests include, but are not limited to, international political communication, new media research, and cross-cultural studies.

Jinghong Xu (PhD) is a professor at the School of Journalism and Communication, Beijing Normal University. He is also an adjunct professor at the International College, Krirk University, Bangkok, Thailand. His research interests include new media and internet governance, health communication, intercultural communication, film and television studies, and game research.

Qiong Xu (PhD) is an associate professor at the School of Journalism and Communication, Hunan University. Her research interests include digital media, international communication, and political communication.