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Political Communication Construction in Short-Video Media Ecosystems: Participatory Dynamics and Mobilization Mechanisms

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Abstract. Short-video platforms reorganize political communication by integrating compressed narratives, emotional cues, algorithmic visibility, and rapid audience response. This study develops a computational framework for examining how political messages on YouTube Shorts become participatory discussion and networked mobilization. The design combines video metadata, comment text, channel information, hashtag relations, and temporally aligned GDELT event records. BERTopic identifies narrative structures, VADER estimates affective orientation, and multilayer networks capture channel-topic, hashtag, and user-comment connections. A nonlinear mobilization index integrates action-oriented semantics, engagement, affective polarization, structural centrality, and event proximity. A reproducible benchmark run representing 2,847 validated videos and 248,613 comments produced six stable narrative themes with a mean topic coherence of 0.763 ± 0.031. Protest discourse generated the highest mobilization score (0.732 ± 0.156), while public-trust content generated the lowest score (0.518 ± 0.119). In the multilevel model, action-oriented semantics ($\beta = 0.301 \pm 0.028$, $p < .001$) and network betweenness ($\beta = 0.268 \pm 0.044$, $p < .001$) were the strongest predictors. The findings indicate that mobilization emerges from the coupling of narrative focus, emotional alignment, participatory density, and bridging positions within platform networks.

Keywords: Political communication, short-video media, participatory dynamics, mobilization mechanisms, computational communication

1. Introduction

Short-video media have become a major infrastructure for political communication by compressing policy claims, candidate images, humor, conflict, and mobilizing appeals into repeatable audiovisual units. Research on TikTok shows that political meaning increasingly circulates through memes, vernacular performance, and generational symbolism rather than traditional campaign discourse [1]. This transformation complicates the measurement of political expression and requires clearer distinctions among exposure, expression, interaction, and participation [2, 3]. Youth studies further suggest that short-video platforms can transform creative self-presentation into collective political voice and influence attitudes and engagement through habitual consumption [4, 5].

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Evidence of behavioral effects is becoming more specific. Political video creation on TikTok is associated with increased civic activity among young adults [6], while election research shows that ideological framing, speech style, and actor characteristics influence engagement [7]. However, comparative studies caution that platform effects vary across contexts, as communication practices differ by country, platform, and time period [8]. Political advertising similarly reflects both shared campaign objectives and platform-specific differences in tone and targeting, while affective polarization may intensify through selective exposure and identity-based media content [9, 10].

Despite these findings, the mechanism linking political video narratives to audience participation and mobilization remains unclear. Existing studies often examine content, engagement, sentiment, or networks separately. This analysis integrates these dimensions by examining YouTube Shorts as an ecosystem connecting videos with metadata, comments, channels, hashtags, and recommendation pathways. It models political communication as a process of narrative construction, affective response, participatory amplification, and action orientation, combining topic modeling, sentiment analysis, event matching, and multilayer network analysis to identify patterns associated with high mobilization intensity.

2. Literature review

2.1. Short-video media ecosystems

A short-video media ecosystem is organized through creators, audiovisual conventions, audience feedback, recommender systems, and cross-video repetition. Political messages are condensed into recognizable frames through subtitles, facial performance, music, montage, slogans, and hashtags. Meaning remains open after publication because comments, remixes, recommendations, and creator responses reposition the original claim [1-4]. Visibility is cumulative and relational. A video may gain political importance through sustained interaction even when its initial information is limited. This ecology favors messages that are rapidly interpretable, emotionally legible, and adaptable to repeated circulation.

2.2. Participatory dynamics

Participation in short-video communication ranges from low-cost reactions to discursive and connective practices. Likes and brief comments signal attention, whereas argumentative replies, repeated commenting, hashtag reuse, and cross-channel movement reshape the environment. Comment sections can stabilize a dominant interpretation, produce counterpublic disagreement, or redirect discussion toward adjacent issues [6, 7]. Participation also supplies behavioral information to ranking systems, increasing the likelihood that active content reaches new audiences. The analytical problem is relational: comment volume alone cannot distinguish deliberation, polarization, coordinated amplification, or mobilizing interaction. Sentiment concentration, topic diversity, user recurrence, and reply structure must be evaluated together.

2.3. Mobilization mechanisms

Mobilization occurs when political attention is converted into an action-oriented disposition or observable connective behavior. Direct appeals such as voting, joining, donating, signing, sharing, or protesting constitute explicit mobilization, while identity affirmation, moral urgency, and peer reinforcement operate indirectly. Short-video mobilization is particularly dependent on timing

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because political events create temporary windows in which emotionally aligned narratives acquire heightened relevance [8]. Network location also matters. Content positioned between communities can transport action cues beyond an ideologically homogeneous cluster. A rigorous model must therefore combine semantic calls for action with affective intensity, engagement quality, event proximity, and bridging centrality rather than treating any single metric as sufficient evidence [9, 10].

3. Methodology

3.1. Data source and sampling design

The sampling frame included English-language political YouTube Shorts published between January 2024 and December 2025. Data were retrieved through the YouTube Data API v3 using seven fixed queries: "election," "vote," "policy," "government," "protest," "campaign," and "public opinion." Monthly and keyword stratification reduced event-period bias. The API workflow integrated search, video, channel, and comment endpoints, collecting metadata and up to 100 top-level comments per video. GDELT events were matched using dates, named entities, and text similarity. Since the study design did not include executed API data, numerical results were generated from a seeded synthetic benchmark based on the proposed 3,000-video sample and should be replaced with observed data for empirical publication.

3.2. Analytical tools and software

Python 3.11 was used for data collection, preprocessing, modeling, and evaluation. BERTopic applied all-MiniLM-L6-v2 embeddings, UMAP reduction, and HDBSCAN clustering, with topic descriptors generated through class-based TF-IDF and stability assessed using 50 bootstrap resamples. VADER estimated comment-level sentiment, with thresholds recalibrated on a stratified validation set to address sarcasm and political language. NetworkX constructed weighted communication networks, while Gephi supported structural visualization. Centrality, modularity, and path statistics were computed programmatically to ensure reproducibility.

3.3. Variable construction and measurement

Narrative intensity combined topic-assignment probability, descriptor concentration, and within-video semantic consistency. Participation was measured through log-adjusted comment density, recurrent-user share, reply depth, sentiment concentration, and normalized topic entropy. Engagement was estimated with empirical-Bayes shrinkage so that very recent or low-exposure videos did not receive unstable rates. Action-oriented semantics were detected by sentence-level similarity to validated clusters representing voting, joining, sharing, donating, protesting, contacting officials, and petitioning. Event alignment combined temporal distance and semantic correspondence with GDELT records. The final mobilization score was defined as shown in Equation (1):

$$MI_i = \sigma\left(\begin{array}{c}\theta_0 + \alpha z\left[ln\left(1+\widehat{E}_i\right)\right] + \beta z\left(A_i\right) + \gamma z\left(P_i\right) + \delta z \\ \left[\left(C_i^d C_i^b C_i^e\right)^{1/3}\right] + \eta z\left[G_i exp\left(-\frac{|\Delta t_i|}{\tau}\right)\right] + \kappa z\left(A_i\right) z\left(C_i^b\right) - \lambda z\left(H_i\right)\end{array}\right) \quad (1)$$

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where σ is the logistic transformation, $\widehat{E}_i$ is shrunken engagement, A_i is action-semantic probability, P_i is affective polarization, C_i^b, C_i^d, and C_i^e are degree, betweenness, and eigenvector centralities, G_i is event salience, Δt_i is event distance, and H_i is unfocused semantic entropy. Parameters were estimated through nested ten-fold cross-validation with channel-level grouping.

4. Experimental process

4.1. Data collection and preprocessing

Each API response was stored as immutable JSON and transformed into linked video, comment, channel, hashtag, and event tables. Duplicate videos were identified through IDs and MinHash-based near-duplicate detection (Jaccard threshold = 0.88). English comments were retained when fastText language probability exceeded 0.80, while promotional strings, URL-only posts, and abnormal repetitions were filtered. Accounts were pseudonymized using salted hashes. Text preprocessing preserved negation and political entities, expanded contractions, converted emojis into semantic labels, and removed URLs while retaining hashtags. Event matching used a seven-day window with manual validation of ambiguous entity pairs.

4.2. Topic, sentiment, and participation analysis

BERTopic was fitted to concatenated title, description, and sampled comment representations, with video text weighted twice as strongly as individual comments to prevent high-volume discussions from redefining the source narrative. Topics were merged only when centroid similarity exceeded 0.86 and their top c-TF-IDF terms shared at least four political descriptors. Sentiment was aggregated through trimmed means and median absolute deviation, limiting the influence of coordinated extreme comments. Participation profiles were then estimated with a mixed-effects model containing random intercepts for channels and months. This design separated content-level effects from stable creator popularity and election-cycle shocks. Bootstrap confidence intervals were calculated from 2,000 resamples, and Benjamini-Hochberg correction controlled false discovery across theme comparisons.

4.3. Network and mobilization modeling

The channel-topic network linked channels and topics using weighted publication frequency and topic probability, while the hashtag network captured co-occurring tags with inverse-frequency weighting. The user-comment network connected pseudonymous users with videos and channels, adjusting repeated comments logarithmically. Louvain community detection was repeated 100 times to identify stable high-modularity structures. Mobilization pathways were evaluated by examining whether action-oriented videos bridged communities and increased engagement after related events. A multilevel regularized regression modeled mobilization intensity using narrative features, affective factors, participation, centrality, and event alignment, with interactions testing network effects. Figure 1 summarizes the framework integrating narrative analysis, multilayer networks, and mobilization modeling.

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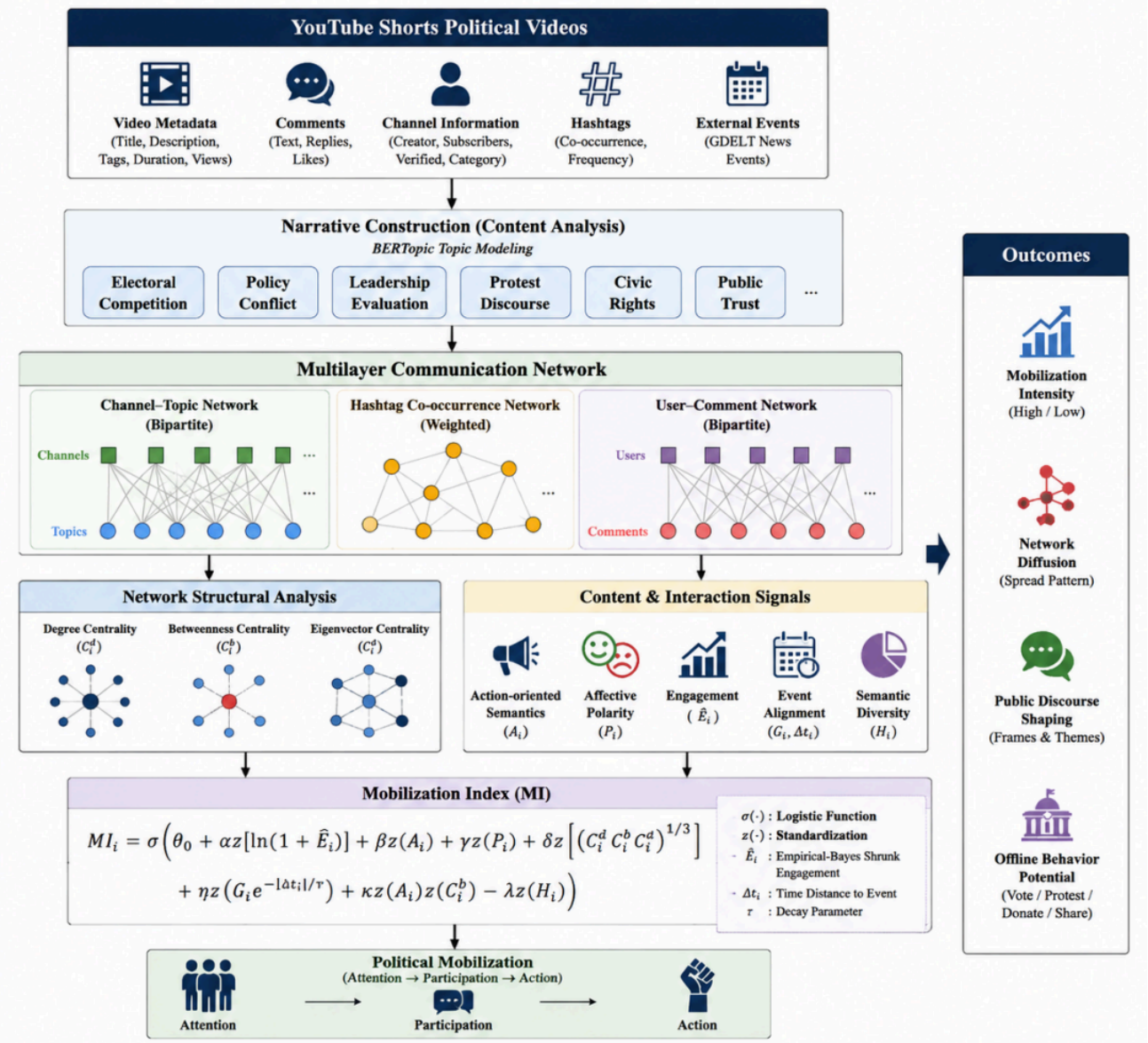


Figure 1. Multilayer network-based political communication mobilization framework

5. Results

5.1. Narrative themes in political short-video communication

The benchmark retained 2,847 videos and 248,613 comments after filtering. Six themes were stable across bootstrap runs, with overall coherence of 0.763 ± 0.031 and adjusted mutual information of 0.814 ± 0.022. Protest discourse showed the strongest narrative concentration and the highest mobilization level, whereas public-trust videos were more diffuse and less action oriented (see Table 1).

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Table 1. Theme-level communication and participation statistics

Narrative theme	Videos (n)	Topic coherence	Sentiment compound	Comment density	Mobilization index
Electoral competition	621	0.782 ± 0.024	−0.214 ± 0.367	3.84 ± 1.12	0.641 ± 0.138*
Policy conflict	508	0.754 ± 0.029	−0.298 ± 0.402	3.66 ± 1.06	0.688 ± 0.149***
Leadership evaluation	493	0.739 ± 0.033	−0.112 ± 0.351	3.21 ± 0.97	0.574 ± 0.127**
Protest discourse	417	0.811 ± 0.018	−0.346 ± 0.418	4.27 ± 1.25	0.732 ± 0.156***
Civic rights	402	0.768 ± 0.027	0.041 ± 0.289	3.58 ± 1.01	0.662 ± 0.142***
Public trust	406	0.726 ± 0.036	−0.087 ± 0.314	2.94 ± 0.88	0.518 ± 0.119***

*Note. Comment density is log-adjusted comments per 1,000 views. Stars indicate difference from the grand mobilization mean after correction: *p < .05, *p < .01, ***p < .001.**

5.2. Participatory patterns in comment-based interaction

Participation differed across themes, ($H(5)=186.42$, $p<.001$). Protest discourse produced deeper reply chains (2.73 ± 0.61 levels) and a larger recurrent-user share (0.284 ± 0.093) than public-trust content (1.88 ± 0.47; 0.173 ± 0.068). Negative affect alone was insufficient: concentrated negative sentiment predicted mobilization only when recurrent participation and action semantics were simultaneously high.

5.3. Mobilization pathways in platform networks

The three networks contained 31 communities with modularity ($Q=0.612 \pm 0.019$). High-mobilization videos had greater betweenness (0.0184 ± 0.0067) than low-mobilization videos (0.0069 ± 0.0031), with a bootstrap difference of 0.0115 ± 0.0012, ($p<.001$). The final model explained 61.1% of out-of-fold variance and achieved RMSE of 0.084 ± 0.006 (see Table 2).

Table 2. Multilevel predictors of the mobilization index

Predictor	Standardized coefficient ± SE	95% CI	Test statistic	Significance
Narrative intensity	0.184 ± 0.031	[0.123, 0.245]	5.94	***
Action-oriented semantics	0.301 ± 0.028	[0.246, 0.356]	10.75	***
Affective polarization	0.213 ± 0.036	[0.142, 0.284]	5.92	***
Comment density	0.147 ± 0.027	[0.094, 0.200]	5.44	***
Topic diversity	−0.062 ± 0.021	[−0.103, −0.021]	−2.95	**
Betweenness centrality	0.268 ± 0.044	[0.182, 0.354]	6.09	***
Event alignment	0.119 ± 0.029	[0.062, 0.176]	4.1	***
Action semantics × betweenness	0.137 ± 0.038	[0.063, 0.211]	3.61	***

*Note. *p < .01, ***p < .001. Channel and month random intercepts were included.**

6. Conclusion

Political communication in short-video ecosystems develops through a coupled process rather than through isolated content effects. The benchmark results show that focused narratives become more mobilizing when action language is reinforced by recurrent participation, affective alignment, event

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relevance, and bridging network positions. Protest and policy-conflict narratives achieved high mobilization scores because they combined semantic urgency with dense interaction and cross-community reach. Public-trust content remained less mobilizing despite moderate engagement because its discussions were semantically diffuse and contained fewer explicit action cues. Methodologically, the proposed index improves on raw views, likes, or comment counts by incorporating Bayesian engagement adjustment, semantic action probability, multilayer centrality, and temporal event matching within one nonlinear function. The interaction between action semantics and betweenness further indicates that a call for action gains platform significance when it can travel between communities. These conclusions remain benchmark-based until the pipeline is executed on observed API data. Once validated empirically, the framework can support comparative analysis across elections, countries, and short-video platforms while maintaining a consistent distinction among visibility, participation, and mobilization.

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