

Framing the explanation: A computational comparison of influencer and news-media policy explainers on YouTube

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ABSTRACT

As audiences increasingly turn to influencers for political information, how influencers frame policy and how this differs from legacy media remains poorly understood. This study compares the framing of explanatory YouTube videos produced by influencers and legacy media outlets (LMOs) about ten 2025 Trump-administration policies, including DOGE, tariffs, mass deportation, the TikTok ban, and the One Big Beautiful Bill Act and government shutdown. Using a large-language-model-assisted workflow built on the Policy Frames Codebook, which surfaced two emergent frames (Uncertainty and Second-Order Effects; Governing Dysfunction and Institutional Trust), we coded 963 videos for 17 frames and analyzed frame prevalence, topic-adjusted and within-topic differences, and frame co-occurrence networks. Both creator types built their explanations on a shared institutional core of policy prescription, economic, political, and legal frames. Once topic was held constant, influencers were more likely to use Fairness & Equality, Economic, and Uncertainty frames, while LMOs emphasized the Political frame; within topics, differences were modest, and the two groups differed most in which policies they chose to explain. Co-occurrence analysis showed influencers layering values-based frames onto institutional ones rather than replacing them. Influencers thus retain substantive policy content while adding a distributive, forward-looking layer, with implications for public understanding of policy.

KEYWORDS

influencers, explanatory reporting, explanatory YouTube videos, policy frames

1 INTRODUCTION

Influencers have emerged as significant actors in the contemporary information ecosystem, increasingly competing with journalists and news organizations as preferred information sources. In the United States, about one in five adults reports regularly obtaining news from influencers on social media (Stocking et al., 2024). Across platforms such as YouTube, Instagram, and TikTok, larger shares of young users prefer to consume information presented by influencers than by professional journalists or legacy media outlets (Newman, 2024). Out of the motive of helping people deepen their understanding of political knowledge, influencers leverage their popularity to present political and societal content in their communication, ranging from human rights to elections (Fischer et al., 2022; Harff & Schmuck, 2025; Suuronen et al., 2022; Zimmermann et al., 2020). People also perceive that political influencers present political issues in a clearer, more comprehensible, and less

complex manner than legacy media, which is also one of the primary drivers that encourage people to follow political influencers (Schmuck et al., 2022).

Existing research on political influencers has primarily examined their roles as new intermediaries in political communication, who can inform and mobilize people, especially among young audiences (Harff & Schmuck, 2023, 2025; Schmuck et al., 2022; Zimmermann et al., 2020). Research focused on the effects of political influencers found that following political influencers can directly boost young people's online and offline political engagement, suggesting influencers' mobilizing role as parasocial opinion leaders within socially curated flows of information (Harff & Schmuck, 2023; Schmuck et al., 2022). Studies focused on the content characteristics of political influencers' information found that they produce material with high information density focused on basic political education while maintaining relatively low levels of opinion and self-presentation. Compared to legacy media's presentation which is perceived as more objective, fact-based, informative, and neutral, influencers' presentation of political content is perceived as more entertaining, emotional, funny, modern and motivating (Zimmermann et al., 2020).

Schmuck et al. (2022) proposed that people are more inclined to experience simpler and more comprehensible content from influencers. From the perspective of content characteristics, this is because influencers provide more basic educational level political content (Sehl & Schutzeneder, 2023), and interweave lifestyle-based political topics that have an impact on the wider society (Gonzalez et al., 2024; Suuronen et al., 2022). Another reason is that the frames influencers used in their messages are different from frames in legacy media content (Sehl & Schutzeneder, 2023). However, what frames influencers used in their content, and how their frames differ from legacy media content frames have not been studied. Frames are important especially in shaping citizens' judgments and values about public issues. To understand how the frames are different between influencers and legacy media outlets, we decided to look into explanatory videos on the same topic produced by influencers and legacy media outlets.

Explanatory reporting, a relatively new genre, seeks to provide context for the reported issues (Forde, 2007). Its goal is to make complex issues easier for audiences to understand, helping them develop well-informed opinions and accurately attribute responsibility (Dan & Rauter, 2023, p. 1047). Through in-depth explanation, journalists help inform audiences and foster an ideal democratic environment (McIntyre et al., 2018). For this study, we focus on policies issued by the Trump administration in 2025. Since President Trump's second inauguration, the administration has issued an unusually high volume of executive orders in rapid succession,

spanning immigration, visa restrictions, and tariffs (Ballotpedia, 2026). Because these orders were enacted quickly and affect millions of people directly, many audiences were caught off guard, uncertain about what the policies actually mean and what their implications might be. Such conditions of high public salience and high uncertainty make these policies compelling subjects for explanatory videos by both media outlets and influencers, given the strong public demand from people who urgently need to understand the changes and how to respond. Yet influencers and legacy media may explain the same policy in very different ways, using different strategies. We therefore ask: what frames do influencers and legacy media use in their explanatory videos (R1), how do these frames differ (R2), and what framing strategies do they employ (R3)?

2 POLICY FRAMES

A frame refers to a central organizing idea that gives meaning to a series of events, and signals what the issue is fundamentally about (Gamson & Modigliani, 1989). Frames emphasize the presentation of certain aspects of a topic. Media coverage of politics uses frames to define how to interpret political issues. Framing is a powerful force shaping public opinion and policy, yet researchers lack systematic ways to identify what frames are selected, how they evolve over time within an issue, and how they diffuse across venues or even different policy domains (Boydston et al., 2014). While issue-specific frame inventories offer rich detail, they prevent systematic comparison across debates, and broad typologies like episodic versus thematic frames overlook the substantive content of policy discussions. To overcome these limitations, Boydston et al. (2014) developed a Policy Frame Codebook, including frame dimensions such as Economic, Morality, Fairness and Equality, Security and Defense, and Political, that can be applied to any policy issue and communication venue. These dimensions allow researchers to nest issue-specific arguments within a common structure, enabling comparative analysis of frame selection, temporal evolution (including bandwagon effects during attention surges), and diffusion across venues or issues.

The Policy Frames Codebook proposes fifteen general dimensions that capture the main ways any policy issue can be framed. These include Economic (costs, benefits, and financial implications); Capacity and Resources (availability or shortage of physical, human, financial, or systemic resources); Morality (religion, ethics, duty, and social responsibility); Fairness and Equality (equal or unequal treatment, rights, and distribution across groups); and Constitutionality and Jurisprudence (legal authority and judicial interpretation). Others address Policy Prescription and Evaluation (proposed solutions and their effectiveness); Law and Order, Crime and Justice (enforcement, sentencing, and crime); Security and Defense (threats and protective actions); Health and Safety (illness, healthcare, and infrastructure risks); and Quality of Life (daily well-being, mobility, and community life). The remaining dimensions are Cultural Identity (social norms and values), Public Opinion (polls and political responsiveness), Political (partisan maneuvering, lobbying, and elections), External Regulation and Reputation (international relations and comparative outcomes), and an Other category for any remaining frames. These

dimensions are intentionally broad and overlapping, allowing issue-specific arguments to be nested within them while enabling systematic comparison across policy debates.

Because our study examines the Trump administration’s policies since 2025, which cut across multiple policy domains, we adopt the Policy Frames Codebook as our primary framework for analyzing which frames and framing strategies media outlets and influencers use in their explanatory videos.

3 METHOD

3.1 Data Collection

Before retrieving videos and downloading transcripts, we designed a set of search query templates to target explanatory videos on YouTube. The templates were: [topic] explained, [topic] deep dive, [topic] breakdown, [topic] how it works, [topic] pros and cons analysis, why [topic] happened, and why [topic] now. We executed these queries on YouTube and used the YouTube Data API to retrieve lists of candidate videos along with their associated metadata (title, channel, upload date, view count, video ID, and description). From this list, we then used yt-dlp (<https://github.com/yt-dlp/yt-dlp>) to download the available transcripts, including both community-provided and auto-generated captions. Finally, we concatenated the transcript segments for each video and stored the complete transcript text alongside the video metadata for subsequent analysis. The timeframe for each topic was set from 2025 January 1st to 2026 January 1st.

3.2 Data cleaning

Video metadata for each topic was filtered through a uniform pipeline. Records were deduplicated on video ID, then screened on format: videos under two minutes (Shorts, brief clips) and over sixty minutes (livestreams, podcasts) were removed as structurally unlike explanatory content. Only videos tagged with an English audio-language variant were retained. Topical relevance was then verified in two steps using topic-specific core terms matched against each video’s title and description: videos with no match in either field were removed as keyword false positives, and videos matching only in the description were removed as well, on the reasoning that a title declares a video’s primary subject while a description mention typically signals a passing reference. This title-match rule trades recall for topical precision, a deliberate choice given that the analysis requires videos whose explanatory project is the topic itself.

3.3 Channel categorization

Channels were classified based on ownership, organizational structure, and communicative identity into three groups. (a) Media organizations include newsroom-based outlets that produce journalistic content under institutional editorial processes. The category encompasses both national mainstream media (e.g., BBC, CNN) and local or niche newsrooms that follow professional journalistic routines. (b) Influencer explainers comprise creator-owned, personality-driven channels that regularly address public affairs or current issues through explanatory or commentary-style videos. This category includes both “journoinfluencers”

with journalistic backgrounds and non-journalist creators who act as independent explainers of political, economic, or social topics.

3.4 LLM-assisted framing analysis

We coded frames using the LLM-assisted workflow of Gómez-Zarà et al. (2026), which treats a large language model as an analytic collaborator rather than an automated classifier. The workflow moves through seven phases, in which researchers use the model’s explanations to surface ambiguities and refine a theory-driven codebook while retaining interpretive authority over every revision.

Phase 1: Establishing theoretical boundaries. We adopted the Policy Frames Codebook (Boydston et al., 2014) and compiled its 15 dimensions, with their definitions and examples, into a coding protocol. Each frame was coded as present or absent in a video, without ranking frames against each other.

Phase 2: Corpus exposure and pattern surfacing. We drew a training sample of 199 transcripts from the ten topics. The model coded each transcript against the 15 frames with supporting evidence and flagged recurring patterns the codebook did not capture, yielding 17 candidate emergent frames. Two authors reviewed every candidate frame by reading the original transcripts in which it appeared and discussing whether it described a distinct way of framing policy. Through this discussion, the two authors agreed to add two new frames to the codebook: Uncertainty and Second-Order Effects, and Governing Dysfunction and Institutional Trust.

Phase 3: Selection of representative and borderline cases. For each of the 17 frames, we selected clear, ambiguous, and difficult cases and counter-examples from the training sample, each supported by verbatim quotes. We reviewed every case and corrected those in which the initial code did not follow the frame definition.

Phase 4: Codebook prompt and application. Following the prompt structure proposed by Gómez-Zarà et al. (2026), we built a codebook prompt containing a role instruction, general coding instructions, each frame’s definition with positive and negative examples, two framing questions per frame, and a JSON output format requiring a justification for every answer.

Phase 5: Analytic interrogation. Two authors carefully reviewed the frames coded by the model and the justifications it gave for each decision. They identified recurring errors, such as coding a frame because a passage named a relevant topic rather than making the frame’s claim, or inferring a claim the passage did not state. For controversial codes, the two authors discussed the case against the frame definition and the transcript, and decided whether and how to refine the prompt.

Phase 6: Codebook refinement. The rules agreed on in Phase 5 were added to the prompt, including that a frame is coded only when a passage states its claim and that decisions must be based on the surrounding context rather than a single sentence. We tested the revised prompt on 20 held-out transcripts and reviewed the disagreements, which led to further clarifications, for example on when failures of oversight count as governing dysfunction.

Phase 7: Stabilization, scaling, and validation. We applied the final prompt to all 966 cleaned transcripts through the Anthropic API (Claude Sonnet 5), and 963 were coded successfully. Consistency was checked by comparing the pilot codes with the

exploratory codes, inspecting the model’s justifications, and verifying that quoted evidence appeared in the transcripts.

3.5 Descriptive overview

The final combined corpus comprised 963 coded YouTube explanations of ten Trump-administration policies published by 658 distinct channels. Of these videos, 60.3% came from 493 influencer channels, and 39.7% from 165 news-media channels. The corpus was unevenly distributed across topics: the One Big Beautiful Bill Act and government shutdown was the largest ($n = 204$), followed by DOGE ($n = 161$), tariffs ($n = 160$), and the dismantling of the Department of Education ($n = 112$), while AI policy ($n = 34$) and the Paris climate withdrawal ($n = 30$) were the smallest. Transcripts totaled approximately 1.68 million words, and influencer videos were about twice as long as media videos (median 1,531 vs. 768 words). On average, a video contained 6.2 of the 17 frames ($SD = 2.47$, median = 6), with little difference between influencers ($M = 6.26$) and news media ($M = 6.10$). Frame use was strongly topic-dependent: Crime and Punishment appeared in 99% of videos on the D.C. crime emergency, Health and Safety in 98% of videos on gender-affirming care, External Regulation in 97% of Paris withdrawal videos and 88% of tariff videos, and Security and Defense in 80% of TikTok ban videos. Frame density also differed by topic, ranging from 5.4 frames per video for the budget bill and shutdown to 7.6 for mass deportation.

4 RESULTS

4.1 Major frames detected in each topic

Frame use differed strongly across the ten topics (Table 2). Policy prescription & evaluation was present in nearly every video in every topic (97–100%), and the Political frame appeared in at least half of the videos in each topic (52–94%). Beyond this common core, each topic had a distinctive profile, and the profiles fall into three broad groups.

Fiscal and economic policies were framed primarily in economic terms. The Economic frame was present in 97% of videos on the One Big Beautiful Bill Act and government shutdown, 98% on tariffs, and 89% on DOGE. Tariff explanations added External regulation & reputation (88%) and Uncertainty & second-order effects (72%), reflecting their attention to trading partners and to knock-on effects on prices and supply chains. DOGE and the budget bill and shutdown were the topics in which the emergent Governing dysfunction & institutional trust frame was most common (35% and 38%), alongside Capacity & resources (45% and 36%).

Policies that expanded or restructured federal authority were framed as legal and institutional questions. Constitutionality & jurisprudence appeared in 80–89% of videos on the Department of Education, mass deportation, the D.C. crime emergency, and gender-affirming care, and each of these topics added its own substantive frame: Capacity & resources (75%) and Fairness & equality (69%) for the Department of Education, Law & order (73%) and Security & defense (64%) for mass deportation, Law & order (99%) and Security & defense (83%) for the D.C. crime emergency, and Health & safety (98%) and Morality (78%) for gender-affirming care, the only topic in which Morality was a leading frame. Finally, the TikTok ban, AI policy, and the Paris withdrawal were framed through

Table 1. Corpus composition by topic.

Topic	Videos	Media	Influencer	Mean frames / video	Frame instances
OBBBA & government shutdown	204	44	160	5.40	1,102
DOGE	161	18	143	5.82	937
Tariffs	160	132	28	5.61	897
Dept. of Education dismantling	112	50	62	6.96	779
Mass deportation	74	14	60	7.61	563
D.C. crime emergency & cashless bail	70	44	26	7.30	511
TikTok ban	69	22	47	6.10	421
Gender-affirming care restrictions	49	20	29	7.33	359
AI policy	34	13	21	5.91	201
Paris climate withdrawal	30	25	5	6.57	197
Combined	963	382	581	6.20	5,967

Note. Frames counted across all 17 frames of the revised codebook (the 15 original dimensions and the two emergent frames). Frame instances = total number of frames coded present. $N = 963$ coded videos; three of the 966 cleaned transcripts could not be coded.

Table 2. Frame prevalence by topic (% of videos in which the frame is present).

Frame	OBBBA	DOGE	Tariffs	Educ.	Deport.	D.C.	TikTok	Gender	AI	Paris	All
Economic	97	89	98	82	39	20	57	41	76	87	77
Capacity & resources	36	45	13	75	30	23	0	4	21	30	32
Morality	11	19	6	18	32	10	4	78	9	33	17
Fairness & equality	26	25	13	69	45	36	12	65	32	53	33
Constitutionality	25	48	40	86	85	89	71	80	74	37	56
Policy prescription	99	99	100	100	100	100	97	100	100	100	99
Law & order	4	5	3	1	73	99	6	29	0	3	17
Security & defense	10	13	22	1	64	83	80	0	26	0	26
Health & safety	35	15	4	11	22	24	6	98	24	23	22
Quality of life	33	14	6	39	47	50	43	39	9	13	28
Cultural identity	0	2	6	9	11	7	4	27	9	3	6
Public opinion	24	45	28	43	47	60	38	49	29	47	38
Political	59	78	52	94	68	93	70	73	79	57	70
External relations	5	14	88	16	45	13	72	16	62	97	36
Uncertainty & 2nd-order	38	29	72	25	35	11	46	31	29	60	39
Governing dysfunction	38	35	8	28	15	9	1	0	6	10	21

Note. Topics ordered by number of videos, as in Table 1. OBBBA = One Big Beautiful Bill Act & government shutdown; Educ. = Department of Education dismantling; Deport. = mass deportation; D.C. = D.C. crime emergency & cashless bail; Gender = gender-affirming care restrictions; Paris = Paris climate withdrawal. Other (present in 3% of videos) is omitted; the two emergent frames are listed last. $N = 963$.

the United States' relations with other countries: External regulation & reputation appeared in 72%, 62%, and 97% of these videos, combined with Security & defense for the TikTok ban (80%) and with the Economic frame for AI policy (76%) and the Paris withdrawal (87%). These profiles also account for differences in frame density (Table 1): topics framed in one dominant register, such as the budget bill and tariffs, carried fewer frames per video (5.4–5.6) than enforcement and rights topics such as mass deportation and gender-affirming care (7.3–7.6).

4.2 Media vs. influencer comparison

4.2.1 Overall comparison. Media and influencer transcripts share the same four most frequent frames: Policy prescription & evaluation (100% vs. 99%), Economic (74% vs. 79%), Political (73% vs. 69%), and Constitutionality & jurisprudence (58% vs. 54%). They diverge after that. External regulation & reputation is #5 for media (48%) but drops to #10 for influencers (28%). Conversely, Public opinion (#5, 40%) and Fairness & equality (#6, 38%) rank higher for influencers than for media (#7 and #9). The value frames do not move together: Fairness & equality rises in the influencer ranking, Morality sits near the bottom for both groups (#14, 19% for influencers vs. #15, 14% for media), and Law & order ranks slightly lower for influencers (#15, 17%) than for media (#13, 17%). Of these ranking differences, only Fairness & equality is confirmed by the topic-adjusted test; the External regulation & reputation gap reflects topic mix and reverses direction once topic is held constant.

We ran the Cochran–Mantel–Haenszel (CMH) test to compare frame use between LMO and influencer explanatory videos (see

Table 3.1). According to the CMH results, four of the 16 frames differed between LMOs and influencers once topic was held constant. Influencers were more likely than LMOs to use the Fairness & equality frame (common OR = 0.43, 95% CI [0.30, 0.62], $q < .001$), the Economic frame (OR = 0.54, 95% CI [0.35, 0.83], $q = .025$), and the Uncertainty & second-order effects frame (OR = 0.62, 95% CI [0.44, 0.87], $q = .025$). LMOs were more likely to use the Political frame (OR = 1.72, 95% CI [1.19, 2.50], $q = .025$). The remaining ten frames, including Morality, Constitutionality & jurisprudence, Governing dysfunction & institutional trust, and Policy prescription & evaluation, did not differ after adjustment. Two results run opposite to the pooled percentages. Uncertainty & second-order effects (LMO 42% vs. influencer 38%) and External regulation & reputation (48% vs. 28%) appear more often in LMO videos overall only because LMO coverage is concentrated on tariffs and the Paris withdrawal, where both frames are common; within topics, influencers used them at least as often.

4.2.2 Within topic comparison. To understand how LMOs and influencers differ in the frames they use within each topic, we compared the two creator types separately for each of the ten topics. For every topic and each of the 16 frames, we ran a two-sided Fisher exact test and applied Benjamini–Hochberg FDR correction across the 16 frames within the topic, reporting the Haldane-corrected odds ratio (media:influencer) and ϕ as effect sizes. Group sizes are strongly unbalanced in several topics: LMO videos are few for AI policy ($n = 13$), mass deportation ($n = 14$), and DOGE ($n = 18$), and

Table 3.1. Topic-adjusted overall test — Cochran–Mantel–Haenszel (stratified by the ten policy topics; N = 963).

Frame	Common OR (M:I)	CMH χ^2	p	q (BH)	Direction
Fairness & equality	0.43	21.00	<0.001	<0.001 *	Influencer ↑
Political	1.72	8.42	0.004	0.025 *	Media ↑
Economic	0.54	7.57	0.006	0.025 *	Influencer ↑
Uncertainty & second-order effects	0.62	7.51	0.006	0.025 *	Influencer ↑
External regulation & reputation	0.60	5.25	0.022	0.060	(ns)
Capacity & resources	1.52	5.21	0.022	0.060	(ns)
Security & defense	0.67	2.78	0.095	0.192	(ns)
Governing dysfunction & institutional trust	1.36	2.77	0.096	0.192	(ns)
Public opinion	0.78	2.40	0.121	0.215	(ns)
Policy prescription & evaluation	∞	2.02	0.155	0.249	(ns)
Constitutionality & jurisprudence	1.21	1.11	0.292	0.425	(ns)
Morality	0.81	0.97	0.325	0.434	(ns)
Law & order, crime & justice	0.72	0.76	0.385	0.473	(ns)
Quality of life	1.05	0.08	0.778	0.875	(ns)
Cultural identity	1.08	0.05	0.821	0.875	(ns)
Health & safety	1.02	0.01	0.932	0.932	(ns)

Note. Common OR (M:I) = Mantel–Haenszel common odds ratio of LMOs relative to influencers across the ten topic strata (>1 media-skewed, <1 influencer-skewed; ∞ = no LMO video lacked the frame). CMH χ^2 without continuity correction, 1 df. q = Benjamini–Hochberg FDR across the 16 frames; * q < 0.05. Uncertainty & second-order effects and Governing dysfunction & institutional trust are the two emergent frames added in the revised codebook.

influencer videos are few for tariffs (n = 28) and the Paris withdrawal (n = 5), which limits the power of these comparisons. Figure 3.1 shows the gap in frame use for all 160 topic × frame comparisons, and Table 3.2 lists the comparisons that remain significant after correction.

Within topics, LMOs and influencers framed most policies similarly. Only six of the 160 comparisons were significant after correction, and seven of the ten topics showed no significant difference on any frame (Figure 3.1). The One Big Beautiful Bill Act and government shutdown was the only topic with a broad divergence, and it ran toward institutional framing by LMOs: LMO videos were far more likely than influencer videos to use the Capacity & resources (66% vs. 28%), Political (86% vs. 52%), Governing dysfunction & institutional trust (64% vs. 31%), and Quality of life (52% vs. 28%) frames (Table 3.2). This contrast partly reflects which event each group explained within the combined topic. Most LMO videos addressed the shutdown (61% of LMO titles mention it, against 27% of influencer titles), whereas more than a third of influencer titles concern the bill’s tax, deduction, or personal-finance provisions. LMO coverage of the topic therefore centered on the partisan conflict, the strain on federal agencies, and the government’s failure to function.

The two remaining significant differences favored influencers: in the Department of Education corpus, influencers were more likely to use the Economic frame (94% vs. 68%), and in the tariffs corpus, they were more likely to use Governing dysfunction & institutional trust (25% vs. 4%). Several other gaps in Figure 3.1 are large but rest on very small groups, such as the Paris withdrawal, where five influencer videos differ from LMO videos by 56 points on Morality and 44 points on Political; these should be read as suggestive only. The heatmap also shows that the influencer advantage on Fairness & equality found in the topic-adjusted test (Table 3.1) does not come from any single topic: influencers used the frame more often than LMOs in all ten topics, by 8 to 29 percentage points, although no single within-topic gap survived correction. Overall, the differences between LMOs and influencers are modest and consistent across topics rather than driven by sharp contrasts within particular policies, with the budget bill and shutdown as the one clear exception.

4.3 Frames associations

To explore the framing strategies used by media organizations and influencers, we conducted co-occurrence network analysis to see which frames co-occur within each creator type’s corpus. Because frame prevalence differs sharply by topic, associations were estimated within each creator type × topic subset (20 subsets). For every pair of frames, we ran a two-sided Fisher exact test on the 2 × 2 table of presence and absence across the subset’s videos, with ϕ as the effect size (positive = the two frames co-occur; negative = they avoid each other) and Benjamini–Hochberg FDR correction across all pairs within the subset. Frames present in every video or in no video of a subset were excluded. Pairs with q < .05 form the network edges, and communities were identified by greedy modularity maximization on the co-occurrence edges.

4.3.1 Media – within-topic co-occurrence. Tariffs is the only topic in which the media subgroup yields significant associations; in the other nine topics the media subgroups (n = 13–50) produced no pair that survived correction. Eight frame pairs are significant within media tariff coverage (Table 4.1, Figure 4.1).

Within tariff coverage, the associations sit at the margins of a highly uniform frame profile: Economic (98%) and External regulation & reputation (86%) appear in nearly every media video and form no positive ties. Around this core, media link Capacity & resources with Health & safety ($\phi = .40$), Fairness & equality ($\phi = .38$), and Quality of life ($\phi = .34$), a cluster that connects the economic mechanics of tariffs to their consequences for workers and consumers. A second cluster ties Security & defense to Law & order ($\phi = .35$) and Morality ($\phi = .34$), and a third ties Public opinion to the Political frame ($\phi = .32$) and to Quality of life ($\phi = .31$). Constitutionality stands apart from External regulation & reputation ($\phi = -.27$): coverage of whether the tariffs are legal tends not to be coverage of trading partners and retaliation. Most of these ties rest on small counts (4–7 videos) and so describe a minority of tariff reports; the Public opinion–Political (27 videos) and Constitutionality–External regulation (40 videos) associations involve the most videos.

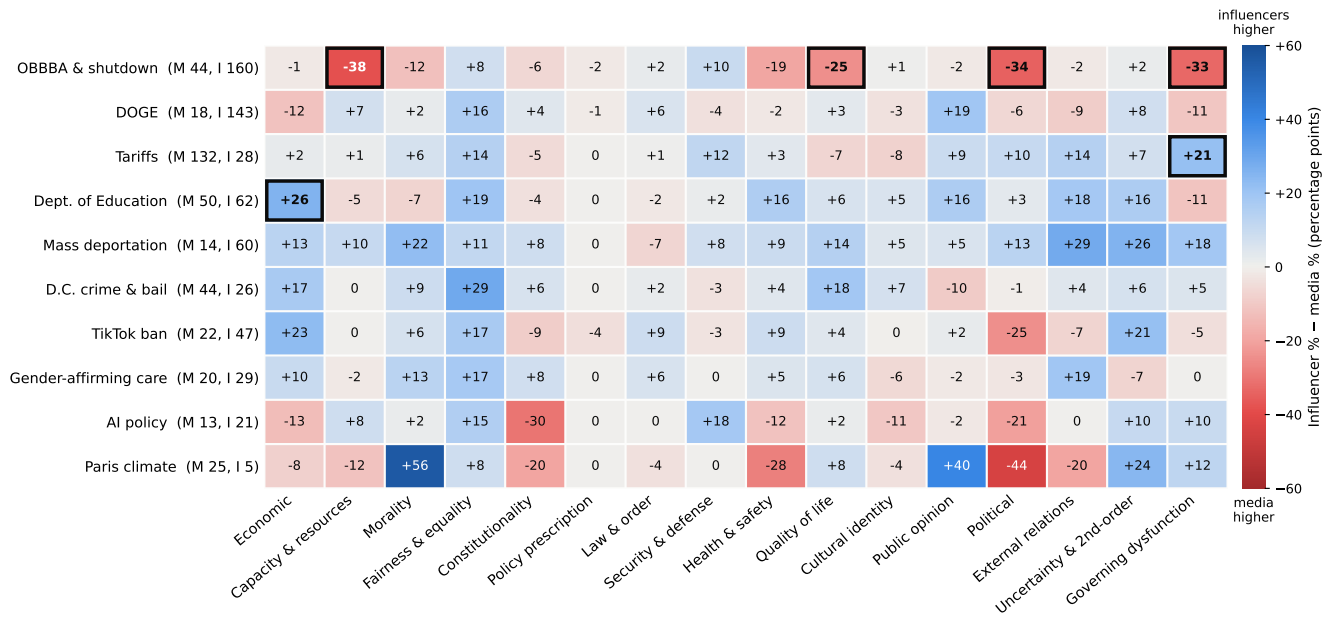


Figure 3.1. Within-topic difference in frame use between influencers and LMOs (influencer % – LMO %, percentage points), by topic and frame. Blue = influencers higher; red = LMOs higher. Outlined bold cells: $q < .05$ (two-sided Fisher exact test, Benjamini–Hochberg FDR across the 16 frames within each topic). M / I = number of LMO / influencer videos.

Table 3.2. Significant within-topic differences between LMOs and influencers (two-sided Fisher exact, BH-FDR corrected within topic; $q < .05$).

Topic	Frame	Media %	Inf %	Gap	OR (M:I)	q (BH)	ϕ
OBBBA & shutdown	Capacity & resources	66	28	-38	4.98	<.001	.33
OBBBA & shutdown	Political	86	52	-34	5.50	<.001	.29
OBBBA & shutdown	Governing dysfunction	64	31	-33	3.89	<.001	.28
OBBBA & shutdown	Quality of life	52	28	-25	2.86	.013	.22
Dept. of Education	Economic	68	94	+26	0.16	.014	.33
Tariffs	Governing dysfunction	4	25	+21	0.12	.017	.31

Note. Gap = Influencer % – Media %. OR (M:I) = Haldane-corrected odds of LMOs using the frame relative to influencers (>1 LMO-skewed, <1 influencer-skewed). q = Benjamini–Hochberg FDR across the 16 frames within the topic. ϕ = phi effect size. The other 154 topic $\times$ frame comparisons were not significant (Figure 3.1).

Table 4.1. Significant frame associations — Media $\times$ Tariffs (n = 132).

Frame A	Frame B	co-occur in	ϕ	Fisher q	Relationship
Capacity & resources	Health & safety	4 videos	+0.40	.025	co-occur
Capacity & resources	Fairness & equality	7 videos	+0.38	.018	co-occur
Law & order	Security & defense	4 videos	+0.35	.025	co-occur
Capacity & resources	Quality of life	5 videos	+0.34	.027	co-occur
Morality	Security & defense	5 videos	+0.34	.025	co-occur
Public opinion	Political	27 videos	+0.32	.018	co-occur
Quality of life	Public opinion	7 videos	+0.31	.025	co-occur
Constitutionality	External relations	40 videos	-0.27	.030	avoid

4.3.2 Influencer – within-topic co-occurrence. Influencers yield significant associations in five of the ten topics (Tables 4.2–4.6, Figures 4.2–4.6): the One Big Beautiful Bill Act and government shutdown (36 pairs), DOGE (3), the Department of Education (3), mass deportation (2), and the TikTok ban (2). No pair survived correction for AI policy, the D.C. crime emergency, gender-affirming care, the Paris withdrawal, or tariffs, where the influencer subgroups are small (n = 5–29). Every significant influencer association is positive: within influencer videos, frames either travel

together or are unrelated, and no pair of frames significantly avoids each other.

The OBBBA and shutdown network is by far the densest (Table 4.2, Figure 4.2) and divides into two communities. The first joins Fairness & equality, Morality, Public opinion, Quality of life, Security & defense, and Law & order: explanations that ask who gains and who loses under the bill, whether that is fair, and how the public is reacting (Morality–Fairness $\phi = .43$; Fairness–Public opinion $\phi = .42$). The second joins the Political frame with Health & safety, Capacity & resources, Governing dysfunction, Uncertainty

Table 4.2. Significant frame associations — Influencer × OBBBA & shutdown (n = 160).

Frame A	Frame B	co-occur in	ϕ	Fisher q	Relationship
Economic	Policy prescription	154 videos	+0.70	<.001	co-occur
Capacity & resources	Governing dysfunction	29 videos	+0.47	<.001	co-occur
Fairness & equality	Health & safety	29 videos	+0.46	<.001	co-occur
Morality	Public opinion	11 videos	+0.43	<.001	co-occur
Morality	Fairness & equality	12 videos	+0.42	<.001	co-occur
Fairness & equality	Public opinion	23 videos	+0.41	<.001	co-occur
Quality of life	Governing dysfunction	27 videos	+0.41	<.001	co-occur
Capacity & resources	Quality of life	25 videos	+0.40	<.001	co-occur
Health & safety	Political	40 videos	+0.40	<.001	co-occur
Law & order	Security & defense	5 videos	+0.39	.001	co-occur
Security & defense	Health & safety	15 videos	+0.39	<.001	co-occur
Fairness & equality	Political	37 videos	+0.38	<.001	co-occur
Quality of life	Public opinion	21 videos	+0.36	<.001	co-occur
Public opinion	Political	31 videos	+0.35	<.001	co-occur
Health & safety	Quality of life	25 videos	+0.35	<.001	co-occur
Morality	Health & safety	11 videos	+0.35	<.001	co-occur
Political	Governing dysfunction	38 videos	+0.34	<.001	co-occur
Fairness & equality	Quality of life	23 videos	+0.33	<.001	co-occur
Fairness & equality	Security & defense	13 videos	+0.33	<.001	co-occur
Capacity & resources	Health & safety	24 videos	+0.32	<.001	co-occur
Quality of life	Political	34 videos	+0.31	<.001	co-occur
Morality	Political	13 videos	+0.29	<.001	co-occur
Fairness & equality	Uncertainty & second-order	27 videos	+0.28	.003	co-occur
Constitutionality	Health & safety	20 videos	+0.28	.004	co-occur
Public opinion	Governing dysfunction	20 videos	+0.28	.004	co-occur
Morality	Quality of life	9 videos	+0.28	.005	co-occur
Security & defense	Political	17 videos	+0.28	.002	co-occur
Morality	Law & order	3 videos	+0.27	.042	co-occur
Political	Uncertainty & second-order	42 videos	+0.27	.005	co-occur
Capacity & resources	Uncertainty & second-order	26 videos	+0.27	.005	co-occur
Capacity & resources	Political	32 videos	+0.26	.005	co-occur
Health & safety	Uncertainty & second-order	27 videos	+0.23	.017	co-occur
Constitutionality	Political	27 videos	+0.23	.017	co-occur
Constitutionality	Governing dysfunction	18 videos	+0.21	.030	co-occur
Health & safety	Public opinion	18 videos	+0.21	.030	co-occur
Security & defense	Quality of life	10 videos	+0.21	.045	co-occur

Table 4.3. Significant frame associations — Influencer × DOGE (n = 143).

Frame A	Frame B	co-occur in	ϕ	Fisher q	Relationship
Capacity & resources	Governing dysfunction	36 videos	+0.41	<.001	co-occur
Health & safety	Governing dysfunction	15 videos	+0.33	.013	co-occur
Quality of life	Governing dysfunction	14 videos	+0.31	.020	co-occur

Table 4.4. Significant frame associations — Influencer × Department of Education (n = 62).

Frame A	Frame B	co-occur in	ϕ	Fisher q	Relationship
Health & safety	Quality of life	11 videos	+0.55	.001	co-occur
Fairness & equality	Quality of life	26 videos	+0.46	.007	co-occur
Capacity & resources	Uncertainty & second-order	20 videos	+0.42	.015	co-occur

Table 4.5. Significant frame associations — Influencer × Mass deportation (n = 60).

Frame A	Frame B	co-occur in	ϕ	Fisher q	Relationship
Economic	Capacity & resources	17 videos	+0.66	<.001	co-occur
Law & order	Public opinion	27 videos	+0.46	.023	co-occur

& second-order effects, and Constitutionality, linking the partisan fight to the bill's consequences for health care, agency capacity, and the functioning of government (Capacity–Governing dysfunction $\phi = .47$; Health–Political $\phi = .40$). The two communities are densely cross-linked, above all through Health & safety and Quality of life, which tie to frames on both sides (e.g., Fairness–Health $\phi = .46$). The Economic–Policy prescription pair ($\phi = .70$) reflects the three videos that carry neither frame rather than a substantive

association, since both frames appear in more than 95% of these videos.

In the smaller influencer networks, the emergent Governing dysfunction frame organizes the ties. In DOGE (Table 4.3, Figure 4.3) it is the hub: videos that describe the federal government failing to function also discuss capacity cuts ($\phi = .41$), health and safety ($\phi = .33$), and quality of life ($\phi = .31$), whereas the dominant Economic, Political, and Policy prescription frames form no ties. In the Department of Education (Table 4.4, Figure 4.4), Quality of

Table 4.6. Significant frame associations – Influencer × TikTok ban ($n = 47$).

Frame A	Frame B	co-occur in	ϕ	Fisher q	Relationship
Economic	External relations	27 videos	+0.57	.014	co-occur
Security & defense	External relations	31 videos	+0.57	.015	co-occur

MEDIA × Tariffs ($n=132$) — frame co-occurrence [$q < .05$]
 blue = co-occur, red dashed = avoid; width $\propto |\phi|$; node size $\propto$ prevalence (% shown)
 same colour = co-occurrence community; grey = no co-occurrence tie

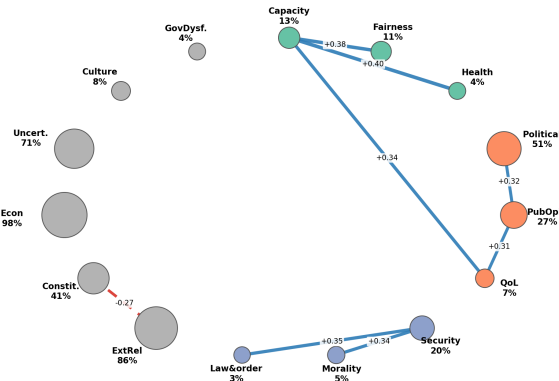


Figure 4.1. Media × Tariffs frame co-occurrence network ($n = 132$). Blue = co-occur, red dashed = avoid; node size $\propto$ prevalence; line width $\propto |\phi|$.

INFLUENCER × OBBBA & shutdown ($n=160$) — frame co-occurrence [$q < .05$]
 blue = co-occur, red dashed = avoid; width $\propto |\phi|$; node size $\propto$ prevalence (% shown)
 same colour = co-occurrence community; grey = no co-occurrence tie

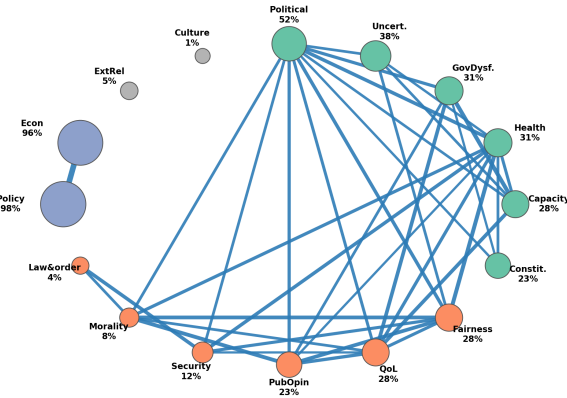


Figure 4.2. Influencer × OBBBA & shutdown frame co-occurrence network ($n = 160$). Two communities: a values cluster {Fairness, Morality, Public opinion, Quality of life, Security, Law & order} and an institutional-consequence cluster {Political, Health, Capacity, Governing dysfunction, Uncertainty, Constitutionality}; Economic–Policy prescription form a separate pair.

life connects Health & safety ($\phi = .55$) and Fairness & equality ($\phi = .46$), tying the dismantling to well-being and to questions of equal treatment, while Capacity & resources pairs with Uncertainty & second-order effects ($\phi = .42$). Mass deportation (Table 4.5, Figure

INFLUENCER × DOGE ($n=143$) — frame co-occurrence [$q < .05$]
 blue = co-occur, red dashed = avoid; width $\propto |\phi|$; node size $\propto$ prevalence (% shown)
 same colour = co-occurrence community; grey = no co-occurrence tie

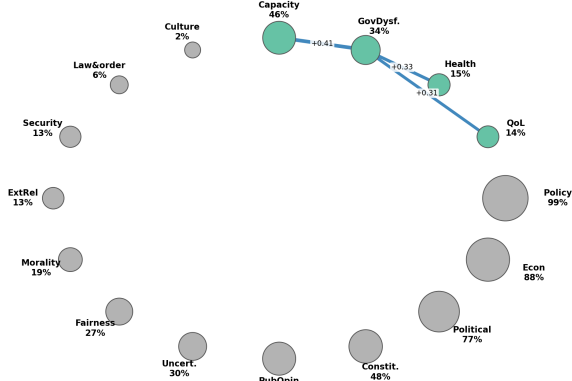


Figure 4.3. Influencer × DOGE frame co-occurrence network ($n = 143$). Governing dysfunction is the hub, tied to Capacity, Health and Quality of life.

INFLUENCER × Dept. of Education ($n=62$) — frame co-occurrence [$q < .05$]
 blue = co-occur, red dashed = avoid; width $\propto |\phi|$; node size $\propto$ prevalence (% shown)
 same colour = co-occurrence community; grey = no co-occurrence tie

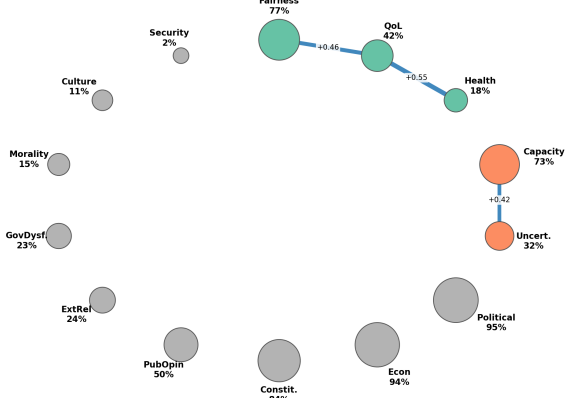


Figure 4.4. Influencer × Department of Education frame co-occurrence network ($n = 62$). Quality of life links Health and Fairness; Capacity pairs with Uncertainty.

4.5) yields two unrelated pairs, Economic–Capacity ($\phi = .66$) and Law & order–Public opinion ($\phi = .46$). In the TikTok ban (Table 4.6, Figure 4.6), External regulation & reputation links Economic ($\phi = .58$) and Security & defense ($\phi = .57$), the geopolitics-and-trade framing of the ban.

Across creator types, media networks are sparse and appear only in the topic where media coverage is concentrated, whereas

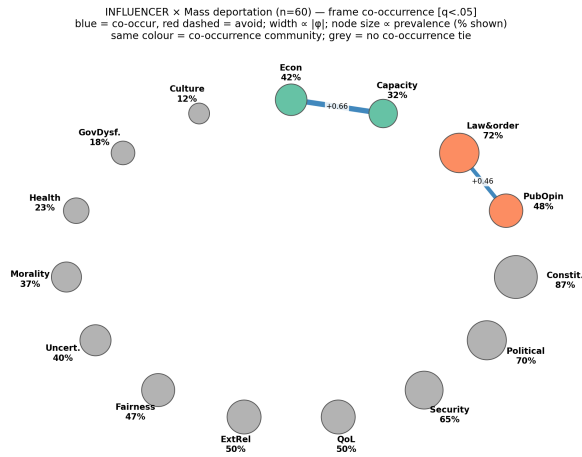


Figure 4.5. Influencer x Mass deportation frame co-occurrence network (n = 60). Two separate pairs: Economic–Capacity and Law & order–Public opinion.

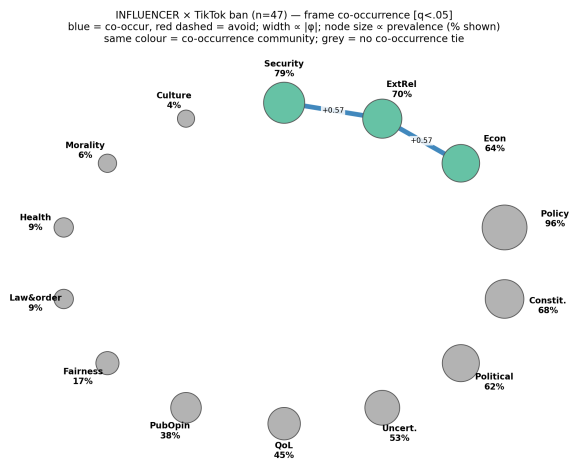


Figure 4.6. Influencer x TikTok ban frame co-occurrence network (n = 47). External relations links Security and Economic.

influencer networks are denser and, in the largest influencer topic, organized into a values cluster alongside an institutional-consequence cluster. This is consistent with the topic-adjusted finding that influencers more often use the Fairness & equality frame (Table 3.1). Because the number of detectable pairs depends heavily on subgroup size, the absence of a network in a topic should be read cautiously rather than as evidence that the frames are unrelated.

5 DISCUSSION

This study compared how influencers and legacy media outlets (LMOs) framed their explanations of ten Trump-administration policies on YouTube. Three patterns stand out. Both creator types

built their explanations on the same institutional core. The differences between them were modest, concentrated on a few frames, and largely consistent across topics. And the two groups differed most sharply not in how they framed a given policy but in which policies, and which aspects of a policy, they chose to explain.

Regarding which frames the two groups used (R1), LMO and influencer videos shared the same four most frequent frames: Policy Prescription & Evaluation, Economic, Political, and Constitutionality & Jurisprudence. Influencer videos were also about twice as long as LMO videos and carried as many frames per video (6.26 vs. 6.10). Research has suggested that audiences find influencers' political content simpler and easier to follow than legacy media coverage (Schmuck et al., 2022; Sehl & Schutzeneder, 2023). Our findings indicate that this perceived simplicity does not come from a narrower framing of policy: influencers reproduced the same institutional explanation that LMOs offered. Frame use was driven more by the policy than by the creator. Crime and Punishment appeared in nearly every video on the D.C. crime emergency, Health and Safety in nearly every video on gender-affirming care, and External Regulation in nearly every video on the Paris withdrawal and tariffs, regardless of who produced them. This is consistent with the premise of the Policy Frames Codebook that each issue carries its own repertoire of relevant dimensions (Boydston et al., 2014).

Regarding how the frames differed (R2), the most robust difference was Fairness & Equality. Once topic was held constant, influencers were more than twice as likely as LMOs to use it, and they used it more often in every one of the ten topics. Morality, by contrast, did not differ once topic was controlled. Influencers' distinctive value frame is therefore distributive rather than moral: it asks who pays, who qualifies, and who is left out, rather than condemning a policy as right or wrong. This partially aligns with Andreeva et al. (2025), who found an emphasis on fairness among left-wing political influencers, although we did not code creators' ideology. Influencers were also more likely to use the Economic frame, consistent with the service orientation of many influencer explainers, which translate policy into its consequences for viewers' own finances. More than a third of influencer titles on the budget bill, for example, concerned its tax, deduction, or personal-finance provisions. Together, the Fairness and Economic frames give influencer explanations a "who gains and who loses" orientation.

Influencers were also more likely to use the emergent Uncertainty & Second-Order Effects frame, explaining what a policy sets in motion and what it means for viewers' plans. This matches the conditions that motivated the study: rapidly issued policies that left audiences uncertain about their implications. It also fits the goal of explanatory reporting to help audiences understand consequences and attribute responsibility (Dan & Rauter, 2023). LMOs, in turn, were more likely to use the Political frame, consistent with the journalistic tendency to cover policy as a contest among political actors (Cappella & Jamieson, 1997). This gap varied across topics and was largest for the budget bill and shutdown, where LMO videos also used Capacity & Resources, Governing Dysfunction, and Quality of Life far more often. That contrast partly reflects what event each group explained: most LMO videos covered the shutdown as a partisan standoff and an institutional breakdown, whereas influencers more often explained what the bill meant for

viewers. The two groups thus differed less in how they framed the same event than in which part of a policy event they chose to explain.

The same division of labor appears across the corpus. Influencers produced 89% of the DOGE videos and 78% of the budget-bill and shutdown videos, while LMOs produced 83% of the tariff and Paris withdrawal videos. Pooled comparisons that ignore topic mistake this specialization for framing differences. External Regulation & Reputation, for instance, appears to be an LMO frame in the pooled data (48% vs. 28%), yet within topics influencers used it at least as often. For audiences, the practical implication is that relying on influencers or on legacy media exposes them to different policies as well as to different frames. For researchers, comparisons of influencer and media content need to account for topic before attributing differences to creator type.

Regarding framing strategies (R3), the co-occurrence networks point to different ways of combining frames. LMO networks were sparse and emerged only for tariffs, suggesting a more standardized explanatory template. Within tariff coverage, LMOs linked Capacity & Resources to Fairness, Health, and Quality of Life, connecting the structural mechanics of tariffs to their consequences for workers and consumers. This reflects the economic-consequences frame operating at both a structural and a personal level (de Vreese, 2005). LMOs also kept the legal question apart from trade diplomacy, as Constitutionality and External Regulation tended not to appear together. Influencer networks were denser, and every significant association among influencer frames was positive: no pair of frames avoided each other. In the budget-bill and shutdown network, a values cluster (Fairness, Morality, Public Opinion, Quality of Life) and an institutional-consequence cluster (Political, Capacity, Governing Dysfunction, Uncertainty, Health) were densely cross-linked, with Health & Safety and Quality of Life bridging the two. Influencers' values framing therefore does not act as a counter-frame that displaces the institutional case (Chong & Druckman, 2007); it is layered onto it, with the human consequences of a policy serving as the link between the two.

The two emergent frames also merit attention. Uncertainty & Second-Order Effects appeared in 39% of videos and Governing Dysfunction & Institutional Trust in 21%. Governing Dysfunction was the hub of the influencer DOGE network, linking capacity cuts to health and quality-of-life consequences. Both frames capture features of governance in 2025 (rapid executive action, a record-length shutdown, the dismantling of federal agencies) that the fifteen generic dimensions do not isolate. This suggests that generic frame typologies may need extension in periods of institutional volatility. It also illustrates the value of an LLM-assisted workflow for surfacing such frames from the data while leaving the decision to adopt them with the researchers (Gómez-Zarà et al., 2026).

Taken together, these findings suggest that influencers do not simplify or trivialize policy explanation. They reproduce the institutional account offered by legacy media and add a distributive, forward-looking layer: who is affected, who is left out, and what comes next. Because fairness framing shapes how audiences evaluate policies and assign responsibility, this layer may matter for

how publics who rely on influencers come to understand government action. The differences we observed are, however, modest in size, and several within-topic comparisons rest on small groups, so they should be read as consistent tendencies rather than sharp contrasts.

6 CONCLUSION

This study examined how political influencers and legacy media outlets (LMOs) frame the same Trump-administration policies in their YouTube explanatory videos. Using an LLM-assisted application of the Policy Frames Codebook (Boydston et al., 2014), extended with two emergent frames, we coded 963 explainers across ten 2025 policies to identify which frames each creator type uses, how they differ, and what framing strategies they employ.

Both groups built their explanations on a shared institutional core: Policy Prescription, Economic, Political, and Constitutional-ity. Once topic was held constant, influencers were significantly more likely to use the Fairness & Equality, Economic, and Uncertainty & Second-Order Effects frames, whereas LMOs leaned toward the Political frame, and influencers used Fairness & Equality more often than LMOs in every topic. Within topics, the two groups framed most policies similarly; the largest contrasts reflected which policies, and which aspects of a policy, each group chose to explain. Co-occurrence analysis revealed distinct strategies: LMOs connected the structural economics of tariffs to their personal costs, while influencers layered values frames onto institutional ones, linking the two through the human consequences of policy. These findings show that influencers do not simplify or trivialize policy explanations; they reproduce the institutional account offered by professional journalists while adding a distributive, forward-looking layer about who is affected and what comes next. As audiences turn to influencers for political understanding, this layer may shape how publics interpret and evaluate government action.

Three limitations temper these results. First, media and influencer videos were unevenly distributed across topics, so several within-topic comparisons rest on small groups and have limited power to detect differences. Second, frames were coded by an LLM within a researcher-guided workflow; although two authors reviewed coded cases and the model's justifications, the coding was not validated against an independent human-coded sample, and intercoder reliability was not estimated. Third, videos were treated as independent observations even though some channels contributed several videos, and we examined only generic policy frames; future work should account for channel-level clustering and incorporate issue-specific frames to capture additional dimensions of media-influencer framing differences and strategies.

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