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Scale-dependent networked framing in a public crisis: Communication and semantic dynamics on X after the 2024 Trump assassination attempt

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Abstract

How do communication relations and semantic organization jointly change during a public crisis? Framing research has largely focused on textual frames or static semantic structures, leaving the temporal relationship between interaction networks and meaning configurations underexplored. We analyze 712,372 X posts about the July 2024 attempted assassination of Donald Trump. Across five event phases and six temporal resolutions (5–60 minutes), we construct directed mention networks and term-level semantic co-occurrence networks. Convergent cross mapping (CCM) assesses historical associations between communication and semantic structures, while transfer entropy (TE) tests short-term incremental predictive information. Results vary by phase and temporal scale. CCM associations were most prevalent at 5–10-minute resolutions during early and intermediate post-event periods, but generally did not coincide with robust one-step TE pathways. Robust TE appeared only during days 2–7 after the attack and at 5–10-minute resolutions. Four of five pathways supported in both raw and activity-adjusted series ran from communication measures to subsequent semantic properties; one ran in the opposite direction. During the lower-attention aftermath, CCM associations appeared only within a continuous jointly active segment, while no robust TE pathway emerged at the tested 20-minute resolution. These findings show that networked framing is temporally layered: historical association may coexist with intermittent, metric-specific predictive relationships, without demonstrating stable directional influence.

1 Introduction

Public crises create uncertainty about both facts and interpretation. Before the facts are fully established, public debate already asks what happened, who bears responsibility, how the event should be evaluated, and what action should follow. Goffman (1974) conceptualised frames as interpretive schemata that organise experience and make situations intelligible. Gamson and Modigliani (1989) further argued that public meaning is organised through “interpretive packages” composed of metaphors, exemplars, symbols, and reasoning devices. Entman (1993) defined framing through selection and salience, locating problem definition, causal interpretation, moral evaluation, and treatment recommendation at its core. This tradition shows that the public meaning of an event depends on how factual elements are selected, connected, and oriented towards particular interpretations.

Framing theory already offers multilevel accounts that connect production, texts, and audiences. Scheufele (1999) integrated frame building, frame setting, individual-level processes, and audience feedback into a single process model. De Vreese (2005) linked news production and frame content to media use and its individual and social consequences. From a constructionist perspective, Van Gorp (2007) emphasised interactions among frame sponsors, key events, media content, audience schemata, and cultural resources. Together, these studies established framing as a communication process shaped by actors, institutions, and inherited cultural resources. On platforms, however, frames increasingly emerge through mentions, reposts, replies, and retellings. News organisations, politicians, influential accounts, and ordinary users participate, rather than leaving textual packaging to one media organisation.

Empirical framing research nevertheless continues to focus heavily on textual content and audience effects. Matthes and Kohring (2008) improved the reliability and validity of frame identification by analysing combinations of frame elements. Walter and Ophir (2019) combined topic modelling with community

detection to infer frame elements and their configurations from large corpora. These methods identify which elements of meaning occur together. They reveal less about which actors connect them, how interaction makes them visible, or whether communication relations change alongside semantic reorganisation. Vliegenthart and van Zoonen (2011) similarly argued that frame analysis often underexamines news production, audience practice, and power, thereby obscuring the social conditions under which frames form.

Temporal resolution is central to this gap. Platform activity follows bursty rhythms with long-tailed inter-event intervals (Barabási, 2005). Limited attention and network connectivity jointly shape information competition (Weng et al., 2012), while an expanding information supply shortens cycles of collective attention (Lorenz-Spreen et al., 2019). Mention clustering and semantic reorganisation may occur within minutes, whereas repeated use and structural accumulation unfold more slowly. Public crises also pass-through phases of factual uncertainty, interpretive competition, relative stabilisation, and low-attention reactivation. Aggregating the entire period can therefore cancel relationships that operate in different directions or at different speeds. We ask: how do the communication and semantic structures of framing coevolve across event phases and temporal resolutions?

We examine public discussion on X surrounding the attempted assassination of Donald Trump in 2024. We construct a communication mention network and a term-level semantic co-occurrence network, alongside a separate descriptive analysis of coded frame categories. We divide the observation period into five operational phases: pre-event baseline, immediate high-attention response, early post-event contestation, intermediate post-event period, and lower-attention aftermath. We then analyse each phase at 5-, 10-, 15-, 20-, 30-, and 60-min resolutions. Convergent cross mapping (CCM) assesses system-level historical associations between the two structures. Transfer entropy (TE) tests incremental predictive information between adjacent windows. The largest Lyapunov exponent (LLE) provides a supplementary boundary test of low-dimensional deterministic chaos.

We make two main contributions. First, we introduce scale-dependent networked framing as an observational framework that examines meaning, communication relations, and temporal resolution together. The framework extends content-centered analysis by asking how account connections and lexical associations vary together, and at which temporal resolutions those relationships become observable.

Second, we distinguish system-level historical association from local incremental predictive information. This layered account of coevolution describes how communication and semantic structures can display shared historical variation without forming a stable one-step information chain. It also offers distinct observational criteria for studying candidate feedback processes in framing.

The later-phase findings inform two interpretive accounts—frame reorganisation and relational construction—developed in the discussion.

2 Literature review and research questions

2.1 The multilayered meaning of frames and a relational turn

Framing research spans sociology, psychology, and communication. Goffman (1974) treated frames as interpretive schemata through which people organize experience and understand situations. Gamson and Modigliani (1989) located frames within interpretive packages composed of framing devices, such as metaphors, exemplars, and visual images, and reasoning devices, such as causal explanations and appeals to principle. Public meaning, in this view, is a configuration of related symbolic resources rather than a single proposition. Entman (1993) addressed the conceptual fragmentation across traditions by defining framing as the selection and increased salience of particular aspects of reality. These selections promote specific problem definitions, causal interpretations, moral evaluations, and treatment recommendations. Frames therefore do more than classify topics; they organise meaning and delimit interpretive direction.

Communication research treats framing simultaneously as textual structure, cognitive process, and social practice. Pan and Kosicki (1993) operationalised news discourse through syntactic, script, thematic, and rhetorical structures. They also described it as a social-cognitive process shaped by sources, journalists, audiences, shared culture, and social roles. Scheufele (1999) distinguished media frames from audience frames and connected frame building, frame setting, individual-level processes, and audience feedback. De Vreese (2005) likewise showed how news values, editorial routines, political actors, and audience conditions shape frame building, frame setting, and their consequences. These accounts position frames within an interconnected process of production, textual organisation, audience interpretation, and communication feedback.

Frames are nevertheless often operationalised as countable textual categories, leaving actors, production relations, and communication environments in the background. Such studies tell us less about who produces a configuration of meaning, how interaction makes it visible, and why the same frame follows different trajectories across groups. Vliegenthart and van Zoonen (2011) argued that frame analysis can reduce frames to textual attributes and individual effects when it neglects news production, audience practices, and power relations. Computational methods have made frame identification more systematic. Matthes and Kohring (2008) coded frame elements and identified their combinations, while Walter and Ophir (2019) combined topic modelling and network community detection to infer configurations from large corpora. These advances show how elements of meaning connect, but they do not fully explain how such configurations enter public communication and gain visibility through actor interaction.

We therefore adopt a relational view that returns frames to a communication process constituted by actors, interaction, and meaning resources. This view also distinguishes frames from framing. A frame is an identifiable organisation of an issue at a given moment. Framing is the situated practice through which actors select, connect, revise, and circulate elements of meaning. The frequency of a frame category captures only one dimension of meaning distribution. How actors connect these resources, and how those connections change, are also integral to frame production.

2.2 Networked framing and communication–semantic coevolution

Actors' network positions and relational structures affect how framing resources circulate. Networked framing therefore brings actor interaction directly into frame production. In their study of Twitter discussion during the Arab Spring, Meraz and Papacharissi (2013) showed that elites and ordinary users jointly produced frames

through reposting, replying, and retelling. Actors and frames gained unequal visibility through networked gatekeeping. Barzilai-Nahon (2008) similarly argued that political power, information-production capacity, established relationships, and alternative channels shape an actor's ability to participate in information selection and visibility allocation. Networked framing thus connects meaning production to relational organisation and asks how framing resources are proposed, connected, amplified, and circulated.

Researchers can now compare the semantic networks of different communicators. Hsiao and Hindman (2026), for example, found that YouTube users introduced associations, affective expressions, and conspiracy narratives that appeared less often in media texts. Users can therefore recombine media framing resources. Yet correspondence or divergence between media and user semantic networks describes the state of two meaning systems more readily than it explains continuous change between actor interaction and semantic organisation. We still need to determine whether communication and semantic structures share historical dynamics and whether one provides incremental predictive information about subsequent states in the other.

Research on knowledge networks offers a basis for studying this dual structure. Roth and Cointet (2010) showed that actor relations and knowledge organisation can coevolve through sustained interaction. Communication ties may alter the visibility and combinatorial opportunities of particular elements of meaning. Semantic associations may, in turn, shape the interpretations around which actors interact, cluster, or divide. Researchers must therefore distinguish shared historical change from incremental information about the next state.

We transfer this perspective to public-crisis communication and distinguish two observed structures. The communication structure comprises directed mentions among accounts and records public account references. The semantic structure comprises post-level co-occurrences among extracted terms. These network observations complement the separate analysis of interpretive dimensions through post-level frame coding.

Platform interactions leave observable traces of public discussion. Mentions, replies, reposts, and quotations offer different forms of relational linkage. Here, a mention is an explicit account reference in the post body. A directed author-to-mentioned-account edge records that reference, providing a measure of public relational structure.

Several candidate mechanisms could connect the two networks. Dense interaction can increase opportunities for elements of meaning to co-occur, connecting previously dispersed attributions or evaluations. Established semantic configurations can also provide shared objects, identity boundaries, and points of opposition around which accounts cluster. This reasoning leads to scale-dependent networked framing: communication–semantic relationships can change across event phases and temporal resolutions. Fine resolutions may reveal short-lived directional predictive relationships, whereas coarser resolutions may reveal slower system-level association.

2.3 Event phases and temporal resolution

Networked discussion during a public crisis can be treated as an open complex dynamic system. It contains heterogeneous actors, interaction relations, symbolic resources, platform affordances, limited attention, and continuing external news. Such discussion can involve feedback, uneven activity, bursts, and group

differentiation. Opinion-dynamics research treats collective order as an emergent outcome of local interaction and network structure rather than the simple sum of individual behaviour.

Network models of opinion dynamics show that both consensus and polarisation can emerge from interpretable initial conditions (Das et al., 2014). More recent models have incorporated influencer roles and actor heterogeneity to explain how different node types alter collective trajectories. Their shared insight is that network relations are not neutral containers for opinion change. Connection patterns, differences in influence, and rules of interaction condition transitions in collective states.

Framing research addresses a more specific problem of meaning production: how an event is defined, how responsibility is attributed, which evaluations become salient, and how proposed responses form competing configurations. We draw on the relational emphasis of complex-systems research but move beyond updating predefined opinions. Our focus is the organisation of meaning itself. This shift connects two traditions by asking how changes in actor relations are associated with semantic configurations and whether either structure provides predictive information about the other.

Platform activity is temporally bursty and uneven. Human behaviour often displays concentrated bursts and long-tailed inter-event intervals (Barabási, 2005). Limited attention and network connectivity shape information competition (Weng et al., 2012), and an expanding information supply can shorten cycles of collective attention (Lorenz-Spreen et al., 2019). Traditional and social media attention are also interdependent while following different rhythms (Neuman et al., 2014). Crisis communication therefore contains processes operating at multiple speeds.

Event phase and temporal resolution capture different temporal conditions. Operational phases distinguish periods around the event that may differ in factual uncertainty, actor composition, attention, and available narratives; their labels do not establish discrete theoretical regimes. Resolution refers to the width of the observational time window. A single phase can contain rapid response, intermittent association, and slower accumulation. Minute-level windows retain short-lived clusters of mentions and semantic variation, whereas longer windows integrate multiple rounds of activity. Temporal aggregation can therefore change the type of relationship that becomes detectable.

This approach challenges two assumptions. First, some opinion-dynamics models treat opinions as predefined state variables and networks mainly as mechanisms for updating those states. We instead examine how relational structure varies alongside lexical organisation. Second, some framing research treats communication relations as a background condition or a channel for distributing already formed frames. We analyse communication and semantic structures as changing components of frame production. We ask:

RQ1

How does the system-level association between communication and semantic structures vary across event phases and temporal resolutions?

RQ2

Do the two networks exhibit stable short-term incremental predictive information, and how do its direction, temporal range, and persistence vary?

RQ3

Do the observed fluctuations meet the stated criteria for low-dimensional deterministic chaos?

3 Methods

3.1 Case, data, and unit of analysis

We study the attempted assassination of Donald Trump at a campaign rally in Butler, Pennsylvania, on 13 July 2024. The event combined a sudden shock, intense political polarisation, and sustained retelling, making it suitable for observing competition among frames. We analyse event-related discussion on X from 6 to 30 July 2024. The original dataset contains 712,372 posts; Balasubramanian et al. (2024) describe the data source and collection framework. We standardised timestamps, removed duplicates, and cleaned the fields required for frame identification and network construction.

The time window, rather than the individual post, is our unit of time-series analysis. For every window, we calculated communication- and semantic-network measures and aligned them in a one-to-one panel. We retained activity indicators, numbers of nodes and edges, raw edge records, and jointly active continuous segments. We audited identifiability separately for the pre-event baseline and lower-attention aftermath. A single case allowed us to align operational phases around one external shock and avoid mixing high-frequency relationships across topics, platform rules, and political contexts. We therefore use this case to explore candidate mechanisms and identify their empirical boundaries.

3.2 Frame identification and network construction

We used GPT-5.6 terra through an API for large-language-model-assisted inductive frame coding, without fine-tuning the model. Guided by prompts, the model identified the interpretive frame or frames in each post and generated labels tailored to the attempted assassination. Entman's framing model constrained the induction process. We asked how each post interpreted the event through problem definition, causal attribution, moral evaluation, and treatment recommendation, rather than merely identifying its topic.

Initial post-level coding produced numerous fine-grained labels, including frequent and semantically stable frames as well as rare, peripheral, or near-duplicate categories. We ranked the preliminary labels by frequency and interpretive clarity, retained categories that represented salient forms of public interpretation, and manually merged semantically proximate labels. This procedure yielded 11 core frames.

We assessed agreement between GPT-5.6 terra and independent human coding using a stratified random sample of 2,000 posts spanning event phases and preliminary frame categories. The model and human coding were conducted independently, without consulting one another's assignments. Cohen's $\kappa = 0.87$ summarises LLM–human agreement on this sample. Agreement supports the consistency of the reported coding procedure.

We then constructed a dynamic two-layer system composed of a communication layer and a term-level semantic co-occurrence layer. We extracted mentions from all @ account references appearing in each post's body text, rather than restricting extraction to reply metadata. For each mention, we created a directed edge from the posting account to the mentioned account and weighted the edge by mention frequency. These edges record public account references, not confirmed exposure, reciprocal interaction, or endorsement.

The semantic network represented which extracted terms appeared together. We used spaCy to extract named entities, informative nouns, and affective adjectives from cleaned post text. We retained at most 12 high-information terms per post to reduce the influence of low-information vocabulary and repeated spam. We formed all pairwise combinations of retained terms within each post, treated them as undirected co-occurrence edges, and accumulated edge weights across posts. This term-level network supplied the semantic time-series measures used in CCM, TE, and LLE.

Frame coding and semantic-network construction are distinct operations. The 11 coded frame categories describe interpretive patterns in posts and support the descriptive analysis of frame composition. Multilabel frame coding allows a post to invoke more than one interpretation, such as security accountability and blame for political incitement. Term co-occurrence, however, does not directly establish a connection between such frame functions. We therefore interpret semantic-network measures as properties of lexical organisation relevant to framing.

We also constructed an auxiliary account–semantic-unit bipartite table recording which units each account invoked in each time window. It provided a descriptive link between accounts and semantic material and was not used for the primary time-series measures.

We calculated normalised semantic entropy, semantic-network density, semantic clustering, and normalised eigenvector centrality. These measures describe term diversity, the connectedness of term co-occurrences, local closure among terms, and the structural prominence of terms, respectively. For the communication network, density, mean degree, and clustering describe the coverage of possible mention ties, average connectivity, and local aggregation. Frame entropy and dominant-frame share in the descriptive analysis refer instead to coded frame categories.

We distinguish three analysis modes: raw, activity-only adjusted, and activity-and-size adjusted. Raw series retain the observed combination of activity and network structure. In the activity-only adjusted series, we adjusted communication measures for total mentions and semantic measures for total term-pair counts. The activity-and-size adjusted series additionally accounted for network size and served as a conservative sensitivity analysis. Cross-mode support refers to agreement between raw and activity-only adjusted results; it does not require support in all three modes.

3.3 Event phases and temporal resolutions

We defined phases using theoretical guidance, event anchoring and descriptive data diagnostics. Crisis communication research distinguishes conditions before, during and after a crisis (Sellnow & Seeger, 2013). Issue-attention cycles describe shifts from heightened attention to declining salience (Downs, 1972), while research linking framing and attention documents changing narratives as events develop (Shih et al., 2008). These perspectives motivate phase comparisons but prescribe no universal cut-offs. We anchored five

operational periods to the attack at approximately 22:10 UTC on 13 July 2024: P1, the preceding 7-day baseline; P2, the immediate high-attention response (0–6 h); P3, early post-event contestation (6–48 h); P4, the intermediate post-event period (days 2–7); and P5, the lower-attention aftermath (after day 7 to the sample endpoint). P2–P3 cover initial footage, factual confirmation and early investigation updates (Federal Bureau of Investigation, 2024). P4 overlaps most of the Republican National Convention (15–18 July; United States Secret Service, 2024) and provides a window for examining frame reorganisation as attention recedes; P5 concerns recurrence under lower attention. Declining posting rates and shifts in frame entropy and dominance (Table 1) provide descriptive support for phase heterogeneity.

We aggregated each phase at 5-, 10-, 15-, 20-, 30-, and 60-min resolutions. Fine resolutions of 5–10 min retain short-lived variation in mentioning and term co-occurrence that coarser aggregation may smooth away. Resolutions of 20 min or longer summarise activity over broader windows. We report every estimable resolution to show how temporal aggregation changes observable associations.

The six resolutions also reflect statistical feasibility. P2 contains only 6 h of observations, so 30- and 60-min windows quickly fall below reliable estimation thresholds; we therefore treat 5 min as its primary reference. For P3 and P4, 20 min provides a middle-scale reference while 5–10 min captures faster pathways and 30–60 min assess aggregated patterns. For P5, we analyse the longest jointly active continuous segment at 20 min and supplement it with 5- and 10-min CCM estimates.

3.4 Statistical analysis

CCM and TE address the two main research questions about historical state association and incremental predictive information. LLE provides a supplementary boundary test of a low-dimensional deterministic-chaos interpretation.

First, CCM tests whether two measures retain recoverable information about each other's historical dynamics within a phase. Evidence requires that the states of one series reconstruct the other and that cross-map skill converges as library size increases (Sugihara et al., 2012). We inspected convergence curves, lag direction, and simulation-based direction checks.

Second, TE tests whether a source series' past provides information about a target's next state beyond the target's own history (Schreiber, 2000). We used the Kraskov–Stögbauer–Grassberger nearest-neighbour estimator (Kraskov et al., 2004). One-step lag was confirmatory; additional lags were exploratory. Effective TE equals the observed estimate minus the median of a time-shift surrogate distribution. Core TE pathways required the same direction in raw and activity-only adjusted series, with false-discovery-rate correction in both modes (Benjamini & Hochberg, 1995). The activity-and-size adjusted results served as a conservative sensitivity analysis, outside this core criterion. The adjustment variables are described in Section 3.2.

As a supplementary boundary test, LLE assesses whether initially similar states separate at a stable exponential rate (Rosenstein et al., 1993). We treated positive estimates as candidates. An estimate met all LLE criteria only if it satisfied the surrogate, embedding-stability, linear-fit, and cross-mode requirements. The cross-mode requirement used raw and activity-only adjusted series. Surrogate tests assessed whether apparent divergence exceeded that expected from series preserving linear stochastic structure (Theiler et al., 1992). These LLE criteria are distinct from the criteria for core TE pathways.

We interpret CCM as historical state association and TE pathways as conditional incremental predictive information. Neither provides experimental causal identification in this observational design. Shared external inputs, unmeasured confounding, and temporal aggregation can contribute to the observed relationships. Confirmatory comparisons use false-discovery-rate-adjusted statistics, and time-shift surrogates provide null distributions for the association and predictive-information tests. We report short-series estimates as low-powered or non-estimable when applicable; a non-significant result is not evidence that a relationship is absent.

4 Results

4.1 Phase-specific variation in coded frames

The distribution of coded frames concentrated strongly in a small set of frames. Conspiracy was the most common frame (25.67%), followed by partisan conflict (23.65%), blame for political incitement (19.56%), and electoral strategy (10.05%). Heroic martyrdom accounted for 4.04%, security accountability for 3.80%, condemnation of political violence for 3.58%, policy-issue linkage for 0.38%, candidate qualification for 0.05%, identity politics for 0.03%, and political satire for 0.01%. Irrelevant content accounted for 7.77% and other frames for 1.39%. The frame repertoire was therefore dominated by a few interpretations while retaining peripheral and noisy content.

Posting volume and the distribution of coded frames changed markedly across phases. P2 had the highest mean posting rate, at 10,494.83 posts per hour. Posting declined in P3, while mean frame entropy increased to 2.55. Entropy reached 2.73 in P4, the highest value across phases, and the mean dominant-frame share fell to 0.27. The coded frame distribution was most dispersed during this period. P1 had relatively little activity but retained diversity in its coded frames. In P5, activity declined further, frame entropy returned to 2.55, and the dominant-frame share increased to 0.33. Source concentration rose sharply, while the largest semantic eigenvalue remained relatively high.

Before the attack (P1), routine political discussion was dominated by partisan conflict. During the first 6 h after the attack (P2), the hourly posting rate rose almost twentyfold to 10,494.83. Partisan conflict receded and conspiracy framing accounted for 43.72% in the descriptive frame distribution. Frame entropy fell from 2.41 to 2.34, indicating a more concentrated distribution of coded interpretations. The contemporary condemnations of political violence by political elites and mainstream media form part of the descriptive context for these posts.

Between 6 and 48 h after the attack (P3), discussion reached 163,650 posts. Conspiracy remained the leading frame, while blame for political incitement became increasingly prominent in attributions concerning political rhetoric. The dominant-frame share fell to 34.41% and entropy rose to 2.55, indicating greater dispersion than in P2. In the descriptive reading of heroic-martyr posts, the widely circulated image of Trump raising his fist offered a reference point for narratives of personal resilience. We treat this imagery as textual and event context, separate from the network tests.

From days 2 to 7 (P4), posting intensity declined and partisan conflict again became the most frequent frame, leading in 79 of 120 h. Frame entropy reached 2.73 and the dominant-frame share fell to 26.90%. Conspiracy,

condemnation of violence, and heroic-martyr narratives remained present alongside familiar partisan interpretations. This period combined recurrent partisan framing with a relatively dispersed distribution of coded frames.

After day 7 (P5), communication volume and network size approached pre-event levels. We nevertheless observed four medium-sized changes in the descriptive series. Electoral-strategy framing rose around 22 and 24 July, suggesting that interpretive resources accumulated during the acute phases were being reworked within ongoing campaign discussion.

Table 1
Phase-level variation in coded frames and participation.

Phase	Mean posts per hour	Mean frame entropy	Mean dominant-frame share	Mean source concentration	Mean largest semantic eigenvalue	Mean coreness	Mean rank stability
P1: pre-event baseline (7 days before)	513.70	2.41	0.38	0.0027	1,012.44	11.10	0.955
P2: immediate high-attention response (0–6 h)	10,494.83	2.34	0.44	0.0002	10,386.80	18.28	0.937
P3: early post-event contestation (6–48 h)	3,896.43	2.55	0.34	0.0006	4,020.30	15.75	0.979
P4: intermediate post-event period (2–7 days)	1,021.73	2.73	0.27	0.0015	1,344.78	12.45	0.979
P5: lower-attention aftermath (after day 7)	445.01	2.55	0.33	0.0196	729.63	10.97	0.928

4.2 CCM: system-level association shifts across phases and scales

Figure 2 summarises CCM results across phases and resolutions; Table 2 details relationships within P5's jointly active segment. We interpret these cross-map relationships as historical associations, following Section 3.4. P1's long semantic plateaus constrained directional interpretation.

In P2, historical state associations concentrated at 5–10 min. At 5 min, raw and activity-only adjusted series each supported six relationships, but only one metric pair appeared in both modes. At 10 min, three metric

pairs received cross-mode support, based on 36 valid windows. Mentioning and lexical organisation therefore showed fine-resolution association with limited overlap between analysis modes.

P3 yielded 4, 2, 1, 2, 1, and 1 cross-mode supported relationships at 5-, 10-, 15-, 20-, 30-, and 60-min resolutions, respectively. P4 yielded 7, 6, 2, 1, 2, and 1. Both phases showed communication–semantic association at all six resolutions. P4 had more supported metric pairs than P3 at 5–10 min, with smaller and less consistent differences at coarser resolutions.

Within P5's longest jointly active continuous segment, approximately 26 h, we found two cross-mode supported CCM relationships at 5 min and three at 10 min. None received cross-mode support at 15 min or above. Lagged cross-mapping linked earlier communication density with later semantic entropy. In the reverse temporal order, semantic density or entropy was linked with communication density or mean degree; one relationship was synchronous.

The raw and activity-only adjusted results overlapped differently across phases. P2 showed limited overlap, whereas P3 and P4 retained cross-mode support across all six resolutions. Figure 2 separates results within each mode from the metric pairs supported in both.

Table 2
CCM relationships in P5's jointly active continuous segment.

Resolution	Direction	Metric relationship	Cross-map lag	Cross-mode evidence
5 min	Synchronous	Mean communication degree ↔ semantic entropy	0 min	Both raw and activity-only adjusted series retained a synchronous component
5 min	Communication → semantics	Communication density → semantic entropy	15 min	Lagged cross-map association in both modes
10 min	Semantics → communication	Semantic entropy → mean communication degree	30 min	Direction and lag agreed across modes
10 min	Semantics → communication	Semantic density → communication density	30 min	Adjustment produced a bidirectional relationship while retaining this direction
10 min	Communication → semantics	Communication density → semantic entropy	10–20 min	Both modes retained this direction

Note: Arrows denote the temporal order of lagged cross-map associations, interpreted as described in Section 3.4. *Estimates refer to P5's jointly active continuous segment.*

4.3 Transfer entropy: P4 contains short-lived and intermittent directional pathways

We found no core one-step TE pathway in P2, P3, or P5 at the estimable resolutions. P2 met the estimation conditions only at 5 min. P3 produced no core pathway at 5–30 min, and P5's longest jointly active segment produced none at 20 min. We use 'pathway' in the predictive-information sense defined in Section 3.4.

Under the stated criteria, P4 was the only phase with core TE pathways. Four appeared at 5 min and one at 10 min. Four of the five ran from communication to semantic measures. Communication density or clustering provided incremental predictive information about subsequent semantic clustering, centrality, or entropy. The fifth pathway ran from semantic density to communication clustering.

The communication-to-semantic pathways involved mention-tie coverage and local clustering. Communication density showed predictive precedence for semantic clustering at 5 min and semantic centrality at 10 min. Both effective-TE estimates remained positive in the activity-and-size adjusted series. At 5 min, communication clustering also added predictive information about semantic centrality and entropy. The semantic-density-to-communication-clustering pathway supplied the reverse-direction relationship (Table 3).

Effective TE for the core pathways was small, ranging from 0.019 to 0.115 bits in the raw series. Core pathways were confined to 5–10 min. The raw 30-min signal did not retain support in the activity-only adjusted series, and no pathway reproduced in most matched-length windows. The supported relationships were therefore local and intermittent.

Table 3
P4 transfer-entropy pathways robust across raw and activity-only adjusted series.

Resolution	Direction	Communication measure	Semantic measure	Raw effective TE	Activity-only adjusted TE	Activity-and-size adjusted TE
5 min	Communication → semantics	Communication clustering	Semantic eigenvector centrality	0.027	0.049	0.010
5 min	Communication → semantics	Communication clustering	Semantic entropy	0.034	0.058	−0.001
5 min	Communication → semantics	Communication density	Semantic clustering	0.036	0.044	0.038
5 min	Semantics → communication	Communication clustering	Semantic density	0.019	0.122	−0.025
10 min	Communication → semantics	Communication density	Semantic eigenvector centrality	0.115	0.086	0.054

Note: Effective TE is measured in bits. The three analysis modes and core-pathway criteria are defined in Sections 3.2–3.4.

4.4 LLE boundary test: no estimate met all criteria

Figure 4 and Table 4 summarise the supplementary LLE boundary test. P2 produced no positive candidate. P3 and P4 produced isolated positive estimates, but none met all LLE criteria. In P5's jointly active segment at 20 min, the raw estimate was 0.237 h^{-1} (R^2 = 0.758, p = 0.015). The activity-only adjusted estimate was 0.121 h^{-1} (R^2 = 0.277, p = 1.00), failing the fit-quality and surrogate requirements.

Across the phase–resolution comparisons, positive candidates remained sensitive to analysis mode or the additional LLE criteria. The supplementary boundary test therefore provided no robust evidence of low-

dimensional deterministic chaos.

Table 4
LLE candidates across phases and temporal resolutions.

Phase	5 min	10 min	15 min	20 min	30 min	60 min	Objective summary
P1	0/1/0	0/0/0	1/0/0	0/0/0	1/0/0	0/0/0	Semantic plateaus constrain the candidates; no system-level inference about chaos
P2	0/0/0	0/0/0	0/0/0	0/0/0	0/0/0	0/0/0	No candidate within the estimable range
P3	0/1/0	0/0/0	0/0/0	0/0/0	1/0/0	0/0/0	Isolated single-mode candidates; no estimate met all LLE criteria
P4	0/1/0	1/0/0	0/2/0	0/2/0	0/0/0	0/0/0	More candidates, but none replicated across modes
P5	0/0/0	0/0/0	0/0/0	1/0/0	0/0/0	0/0/0	One raw candidate in the 20-min active segment; it failed in the activity-only adjusted series

Note: Each cell reports raw candidates/activity-only adjusted candidates/estimates meeting all LLE criteria. The LLE criteria are defined in Section 3.4.

5 Discussion

The case reveals a temporally differentiated pattern of networked framing. Communication and term-level semantic structures shared historical associations across several phases, while local predictive relationships concentrated in fine-resolution P4 windows. Their limited replication across matched-length windows makes intermittence central to interpreting the relationship.

Scale-dependent networked framing brings actor relations, lexical organisation, attention, and event timing into one observational framework. It directs attention to when these dimensions vary together and when their apparent relationship changes with temporal resolution.

5.1 Scale-dependent networked framing

Scale-dependent networked framing retains Entman's (1993) account of problem definition, causal interpretation, moral evaluation, and treatment recommendation. It adds attention to the relational and temporal settings in which framing-related discourse is observed. Matthes and Kohring (2008) and Walter and Ophir (2019) made frame elements and their configurations more systematically identifiable. We complement this work by examining the temporal resolutions at which mention-network properties are associated with term-network organisation.

The framework extends the observational unit of frame analysis. Conventional content analysis commonly measures texts, frame categories, or phase-level frequencies and asks which frames appear and how often. Scale-dependent networked framing adds the configuration of elements, public mention patterns associated with lexical configurations, and the temporal resolution at which their relationship becomes observable.

Communication relations move from an external condition of frame diffusion into the observational analysis of framing-related discourse. The same nominal frame can take different forms as actor composition, interaction clustering, and semantic connectivity change.

This approach also adds a dynamic distinction to networked framing. Meraz and Papacharissi (2013) showed how elites and publics jointly produce frames through networked gatekeeping, continuing revision, and redistribution. Hsiao and Hindman (2026) showed that platform users can introduce semantic associations, affective expressions, and narratives that media texts use less often. We further distinguish historical state association from local incremental predictive information. Communication and semantic structures can share historical dynamics without a robust one-step TE relationship. The distinction gives networked framing an explicit account of variation in temporal persistence.

Temporal resolution is not a neutral aggregation choice. In P4, TE pathways appeared at 5–10 min, whereas CCM associations also appeared at 20 min and above. Fine resolutions retained local predictive relationships, while coarser windows yielded a different association pattern. This observation connects framing research with work on bursty activity, limited attention, and accelerating collective attention (Barabási, 2005; Weng et al., 2012; Lorenz-Spreen et al., 2019). The aggregation window helps determine which temporal relationships remain visible to the researcher.

Scale-dependent networked framing calls for matching temporal resolution to the theoretical question. A study of short-term predictive relationships requires different observations from a study of historical association. Reporting adjacent resolutions, effective sample sizes, and activity conditions can make findings across studies more comparable. It also clarifies whether apparent disagreement concerns the relationship itself or the temporal window through which it was observed.

5.2 Layered coevolution: system-level association and local predictive information

Layered coevolution distinguishes shared historical variation from local predictive information. Their coexistence need not imply equal persistence: historical association may remain detectable when next-window information gain is intermittent. Shared event histories, recurring attention, and accumulated discussion provide a useful interpretive context for this difference in temporal persistence.

This distinction moves networked framing beyond structural resemblance towards questions about temporal interdependence. Roth and Cointet (2010) connected actor relations with semantic change, while Hsiao and Hindman (2026) documented divergence between media and public semantic networks. Our findings add a temporal question: when does historical association coincide with incremental predictive information for particular network measures?

The distinction also refines the empirical questions posed by process models of framing. Scheufele (1999) linked frame building, frame setting, individual processing, and audience feedback. De Vreese (2005) connected news production, frame content, media use, and consequences. Separating historical association from next-window information gain gives studies of these recursive processes more specific temporal questions. Researchers can examine both the persistence of joint variation and the intervals in which directional predictive information becomes detectable.

Constructionist framing offers a complementary interpretation. Van Gorp (2007) emphasised shared cultural resources and interactions among frame sponsors, key events, media content, and audience schemata. From this perspective, historical association may reflect the continuing availability of interpretive resources across a discussion. Local predictive pathways identify intervals in which one network's history is more informative about the other's next state. Their intermittent appearance motivates closer study of how available framing resources enter particular communication situations.

5.3 Frame reorganisation and relational construction

We treat frame reorganisation and relational construction as interpretive accounts of later-phase patterns, to be tested with actor- and content-level evidence. Frame reorganisation concerns communication–semantic association during renewed joint activity under lower attention. Relational construction concerns the relational conditions associated with visibility and semantic reorganisation.

P5 illustrates the relevance of distinguishing low overall attention from continued joint activity. Within its 26-h active segment, CCM associations appeared in both temporal directions at 5–10 min, while TE yielded no core pathway at 20 min. The informative temporal settings differed between the methods, highlighting the need to connect activity conditions with the resolution of observation.

This pattern connects with constructionist accounts of frames as interpretive packages and cultural resources (Gamson & Modigliani, 1989; Van Gorp, 2007). Lower aggregate attention can coexist with renewed communication–semantic association in active intervals. Frame reorganisation thus motivates looking beyond rising or falling frame frequencies. It asks whether familiar interpretive resources recur in public discussion and how their relational setting changes when they return.

P4 supplies the predictive evidence relevant to relational construction. Four of five core TE pathways ran from communication to semantic measures, linking mention density or clustering with subsequent lexical organisation. This pattern complements the relational emphasis of networked gatekeeping and framing (Meraz & Papacharissi, 2013). It makes mention structure a useful dimension of empirical framing analysis alongside the content and frequency of interpretations.

Relational construction also engages calls to restore production, audience practice, and power to frame analysis (Vliegenthart & van Zoonen, 2011). Density and clustering describe relational settings in which lexical prominence and organisation vary. The reverse-direction pathway and limited matched-window replication make this a contextual account of association. Actor-level research can extend it by examining whose interpretations gain visibility within those settings and how exposure and participation differ across groups.

Together, these interpretive accounts shift attention from a fixed frame life cycle to changing conditions of joint activity and relational association. Later periods can retain diverse interpretations and intermittent network relationships. This perspective makes recurrence, coexistence, and uneven temporal persistence relevant to the study of framing after the initial attention peak.

5.4 Limitations and future research

The findings remain bounded by the case, platform, and data. The attempted assassination combined intense political polarisation, candidate centrality, and elite intervention. Mention practices and visibility mechanisms

on X may also shape the observed relationships. Comparative studies should test the account in natural disasters, public-health emergencies, and other platforms.

Long semantic plateaus in P1 and discontinuous activity in P5 constrained identifiability; the P5 findings describe a selected jointly active segment rather than the entire aftermath. Mention networks record account references rather than verified exposure, and term co-occurrence is an indirect trace of framing-related discourse. LLM–human agreement remains sensitive to coding decisions and model configuration. As specified in Section 3.4, CCM and TE provide observational evidence; common inputs, unmeasured confounding, and aggregation limit causal interpretation. Differences in phase duration and effective sample size also constrain comparisons of supported-pathway counts.

Further work can combine actor stratification, externally coded news events, and cross-model validation. Window-level collection logs would help distinguish low activity from missing data. The researcher-defined phase boundaries also warrant sensitivity tests, including alternative 6-h and 12-h cut-offs, event-triggered windows, and formal change-point analyses. Cross-case studies should preregister confirmatory and exploratory resolutions and compare phases at matched sample lengths. Natural experiments and exposure-sensitive designs could then test the proposed interpretive accounts more directly.

6 Conclusion

The case illustrates scale-dependent networked framing: association and short-term predictive information appear at different phases and resolutions. CCM identified historical associations across several phases. Core TE pathways concentrated in P4 at 5–10 min and showed limited replication across matched-length windows. P5 retained identifiable CCM associations within a jointly active segment, with no core TE pathway at the tested 20-min resolution. The supplementary LLE test provided no robust evidence of low-dimensional deterministic chaos. Together, these findings motivate attention to layered temporal relationships, recurrent joint activity, and the relational settings of semantic change. They extend content-centred framing analysis by making temporal resolution and communication structure explicit parts of the observational framework.

Declarations

Author Contribution

Q.W. conceptualized the study, developed the methodology, implemented the software, performed validation, conducted formal analysis and investigation, curated the data, and prepared the original draft, review, editing, and visualization. Q.W. also administered the project.

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Figures

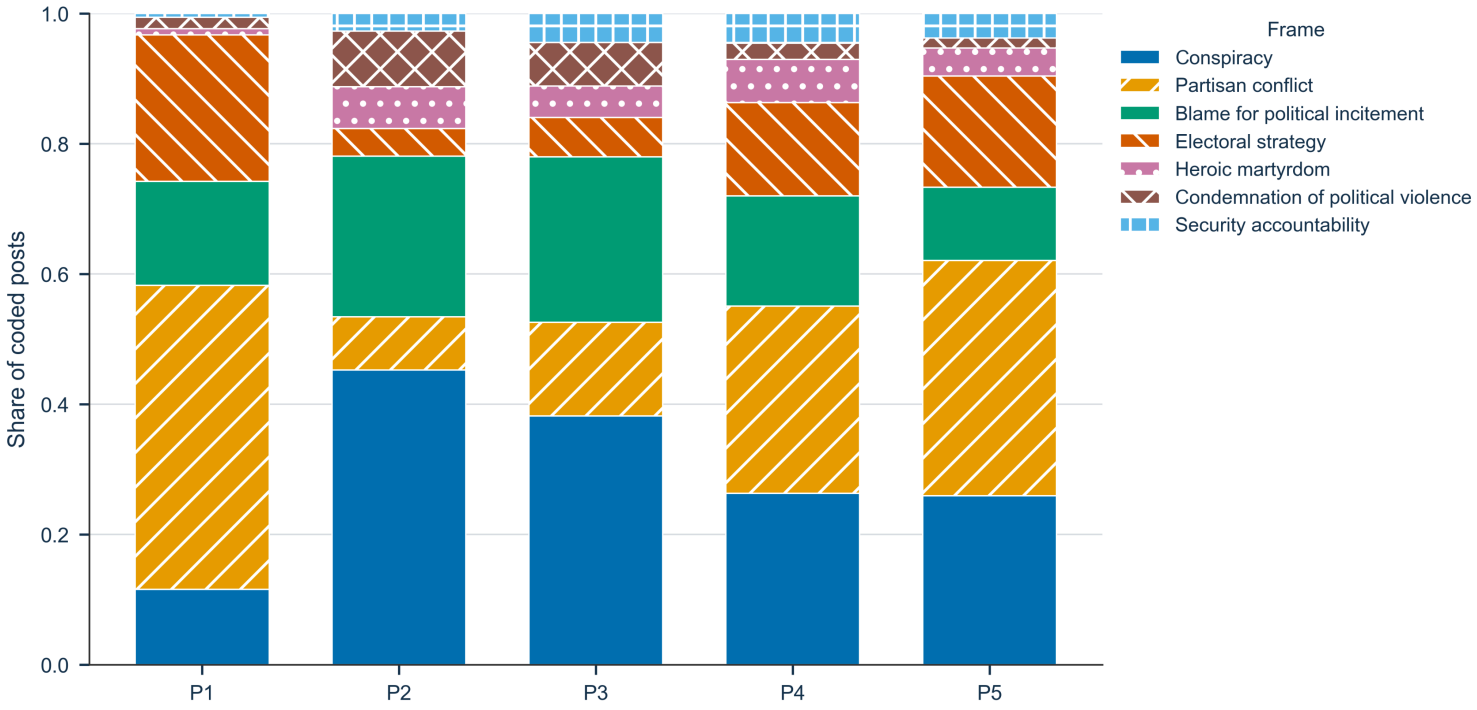


Figure 1

Frame composition across event phases. Bars show the within-phase shares of seven recurrent frame categories after excluding irrelevant, residual, and very low-frequency categories. P1, pre-event baseline; P2, immediate high-attention response; P3, early post-event contestation; P4, intermediate post-event period; P5, lower-attention aftermath.

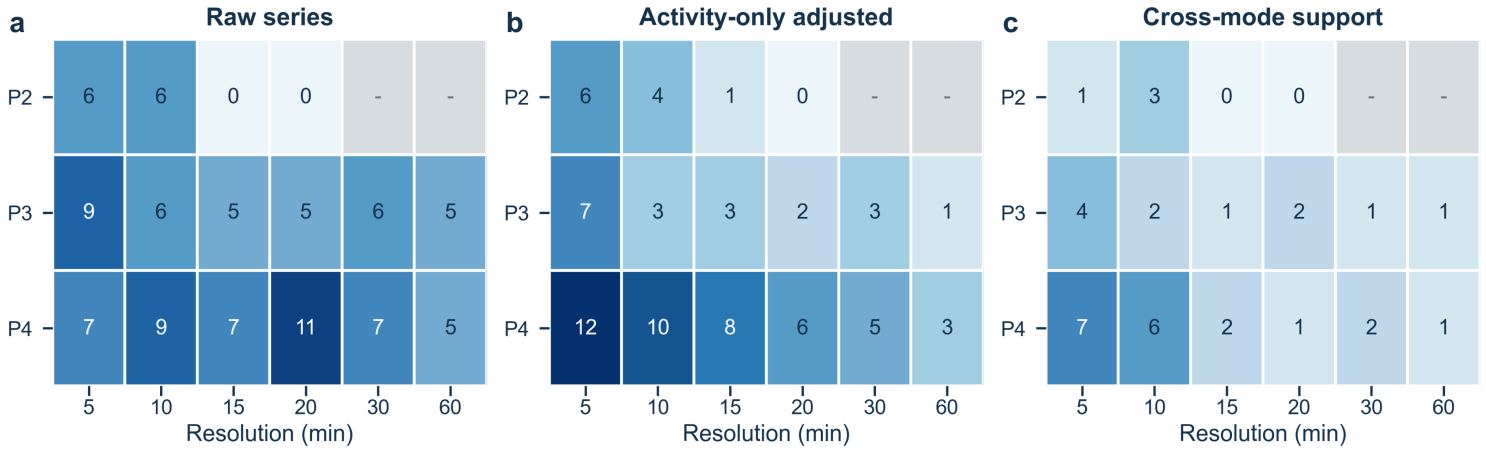


Figure 2

CCM relationships across phases and temporal resolutions. a, Number of supported relationships in raw series. **b**, Number in activity-only adjusted series. **c**, Number of metric pairs supported in both modes. A hyphen (-) marks a non-estimable phase–resolution combination; zero denotes no supported relationship under the stated criteria. P5 is reported separately because only its jointly active segment was identifiable.

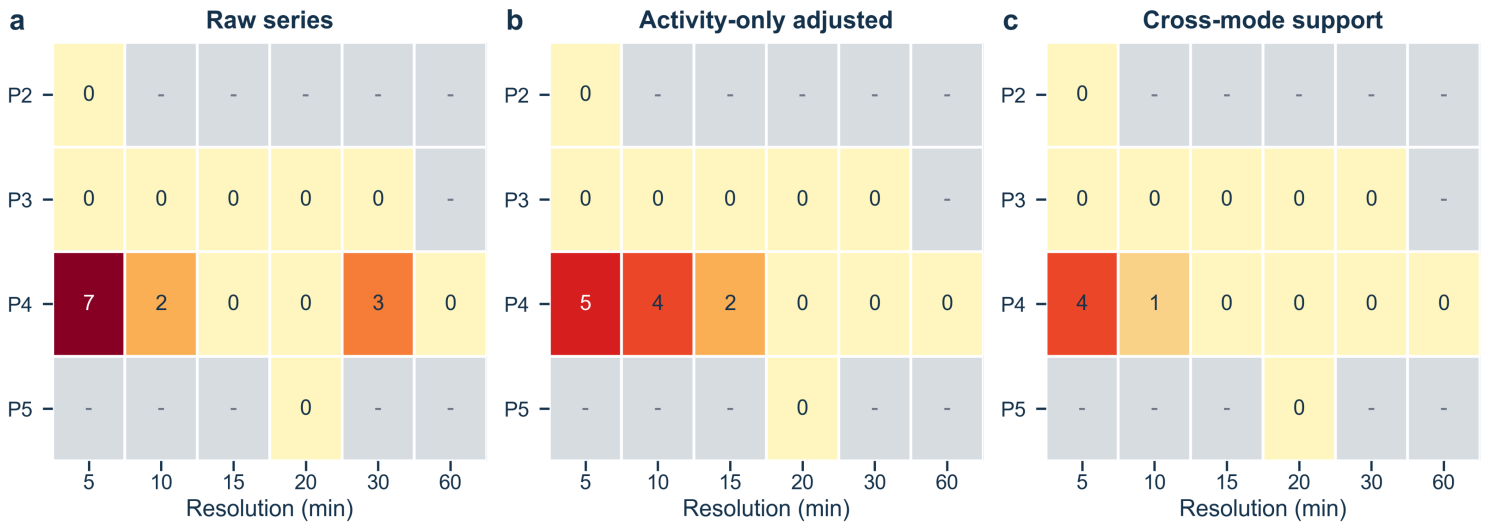


Figure 3

One-step transfer-entropy pathways across phases and temporal resolutions. a, Number of significant pathways in raw series. **b**, Number after activity-only adjustment. **c**, Number supported in both modes. A hyphen (-) marks a combination that was not estimable or not tested; zero denotes no supported pathway. P2 was estimable only at 5 min, P3 was not estimable at 60 min, and P5 was tested only at 20 min within its jointly active continuous segment.



Figure 4

LLE candidates and robustness across phases and temporal resolutions. a, Positive candidates in raw series. **b**, Positive candidates in activity-only adjusted series. c, Estimates meeting all LLE criteria. These include surrogate, embedding-stability, fit-quality, and cross-mode requirements (Section 3.4).