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ARTICLE

Influencer-centered crisis communication: a NodeXL social network analysis of a fiscal controversy between Indonesia's finance minister and regional governors on X (Twitter)

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The digital public sphere has become a primary arena for crisis communication, where information about government officials spreads rapidly through social media platforms such as X (formerly Twitter). This study examines a public controversy between Indonesia's Minister of Finance and regional governors over cuts to regional transfer funds in October 2025 and addresses three questions: (1) What structural pattern characterizes the crisis opinion network, and which actors occupy central positions? (2) How are opinion groups distributed, and which narratives and engagement strategies characterize supportive, critical, and moderate clusters? (3) What role do mass media accounts play relative to government actors? Combining social network analysis (SNA) with qualitative content analysis, the study collected network data from X using NodeXL Pro (keywords "Purbaya" AND "Gubernur"; 1,373 accounts and 1,767 edges over 13 days) and manually coded the stance and narrative strategy of 1,531 posts in the 14 main clusters. The network is highly centralized, but its hub is not a government account: a private, non-verified influencer account, through a single widely retweeted post, attracted 37.9% of all incoming ties, and four private influencer accounts together attracted 61.0%. Each major cluster is a star organized around one source post, and 79.6% of all ties are retweets. Coded stance is strongly one-sided: 74.3% of posts support the minister, 25.1% are neutral or informational, and only 0.6% are critical, so no critical cluster emerged. Supportive clusters defend the minister mainly by ridiculing or discrediting the governors and the national parliament, while neutral clusters form around news outlets, which act as secondary hubs (10.5% of incoming ties). The accounts of the ministry and of the governors are nearly absent, each receiving a single tie. These descriptive findings suggest that, in this case, crisis communication on behalf of an official was carried out largely by third-party influencers rather than by the official or the institutions involved. The study offers an exploratory extension of crisis communication theory and tentative implications for network-aware government communication, within the limits of a single-case, single-platform design.

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Introduction

The proliferation of social media (Durrheim and Schuld 2025; Han and Baird 2024) has fundamentally reshaped the dynamics of crisis communication, turning platforms such as X (formerly Twitter) (Ellis et al. 2024) into central arenas of the contemporary digital public sphere. Unlike traditional mass media, these platforms allow information to circulate instantly, enabling government and public actors to shape, contest, and reframe narratives in real time (Al-Omoush et al. 2023). Habermas's (1991) conceptualization of the public sphere remains a useful entry point, although it requires substantial revision in the context of networked media. In this environment, crises involving public officials are no longer disclosed solely through official press statements; instead, they are co-constructed through decentralized, user-driven networks of retweets, mentions, replies, and quote tweets.

Indonesia offers a particularly instructive context for examining these dynamics. With about 143 million social media user identities in early 2025, equivalent to 50.2% of the population, and an advertising reach on X of about 25.2 million users (Kemp 2025), Indonesia is one of the largest social media markets in the world, and X remains an arena in which controversies over fiscal and economic policy involving national officials can rapidly escalate into polarized public debate. This study examines one such episode: a controversy between a senior Indonesian government official, the Minister of Finance, Purbaya Yudhi Sadewa, and regional governors over cuts to central-to-regional transfer funds (*Transfer ke Daerah*, TKD), which generated intense public discussion on X over a 13-day period in October 2025. This controversy provides an empirical window into how opinion networks form, fragment, and interact during a real-time government crisis.

Many studies have examined crisis communication strategies and message content. Situational Crisis Communication Theory (SCCT), for example, has been extended to argue that the attribution of crisis responsibility is not static but shifts over time (the dimension of perceptual change) and is distributed among multiple parties (the dimension of shared responsibility) (Jong 2025). Comparatively few studies, however, combine social network analysis (Hansen et al. 2019; Rustamaji et al. 2024) with qualitative narrative analysis (Pond and Lewis 2019) to examine how the structure of the network itself relates to crisis discourse, particularly in non-Western contexts with high social media penetration such as Indonesia.

By integrating social network analysis with qualitative content analysis, this study seeks to contribute to crisis communication theory (Logan-McFarlane 2025) by describing how network centralization around third-party influencer accounts, community fragmentation, and the secondary position of mass media and government accounts (Bastos et al. 2013; Reveilhac and Trembovelskyi 2025) jointly characterize crisis communication in one case from the contemporary digital public sphere.

Research objectives and questions. This study aims to analyze the structure of the opinion network that formed on X during the controversy between Indonesia's Minister of Finance and regional governors, combining social network analysis using NodeXL with qualitative content analysis. The main focus of this research is to identify the actors who occupy central positions in

the network, the narrative and engagement strategies of different opinion groups, and the position of mass media accounts relative to government actors. In this context, this study addresses the gap identified above by seeking answers to the following research questions:

- RQ1: What structural patterns characterize the opinion network surrounding the crisis, and which actors occupy central positions within it?
- RQ2: How are opinion groups distributed, and which narrative and engagement strategies characterize supportive, critical, and moderate clusters?
- RQ3: What role do mass media accounts play relative to government actors and other central accounts in the network?

Literature review

Figure 1 summarizes the overall framework of the literature review, linking four theoretical pillars to the three research questions. The top row presents the conceptual foundations from the perspectives of the public sphere and crisis: the digital public sphere (purple) and crisis communication theory/SCCT (coral). The second row presents the methodological and empirical foundations: social network analysis/hub-and-spoke structures (teal) and opinion polarization/mass media (amber). All four pillars converge on the research gap, namely the scarcity of studies that combine SNA with qualitative narrative analysis in non-Western contexts, which is addressed by RQ1–RQ3. These, in turn, lead to the study's theoretical contribution to understanding network centralization, community fragmentation, and the role of mass media.

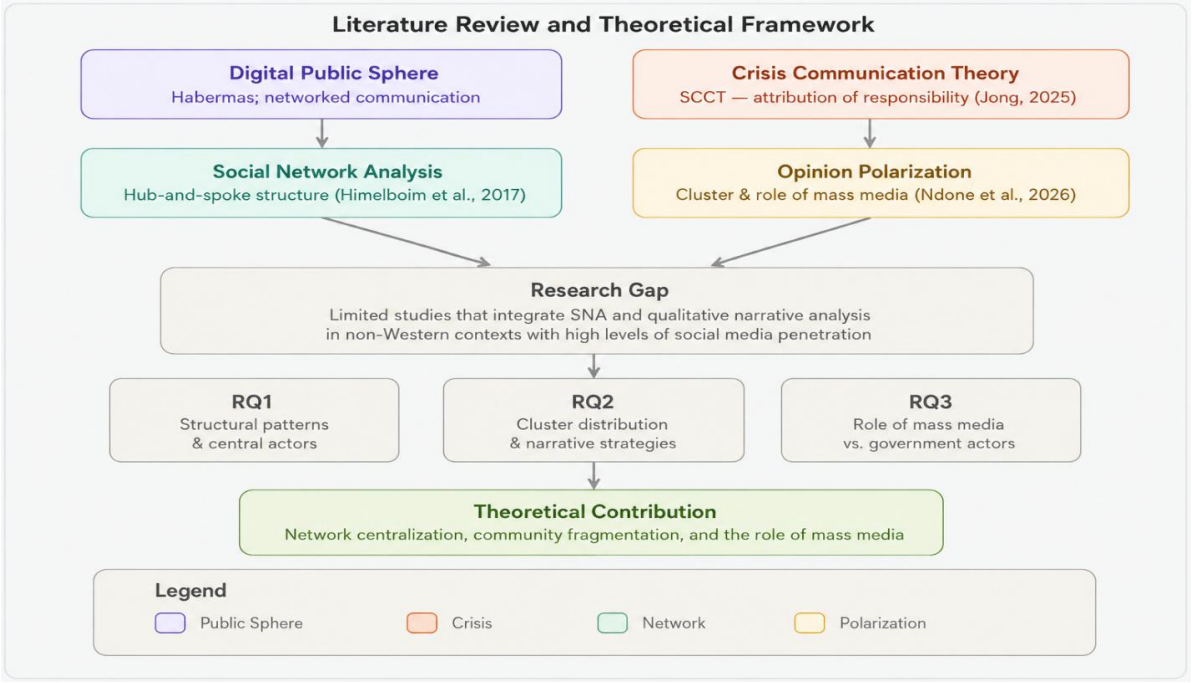


Fig. 1 Literature review and theoretical framework. Source: compiled by the authors.

Digital public sphere and networked government communication. Habermas's (1991) concept of the public sphere (Schäfer 2016) as a space for rational-critical public deliberation has been extensively revisited in the context of social media (Staab and Thiel 2022), which enables both direct and indirect communication between officials and citizens, that is, networked government communication. Unlike the public sphere mediated by the mass media, platforms such as X (Amores et al. 2025) enable government actors (Han and Baird 2024) to bypass traditional journalistic gatekeepers and engage directly with citizens, fundamentally changing the flow of political information during crises (Bastos et al. 2013).

Crisis communication theory in a networked media environment. Classical crisis communication frameworks (Elgueta-Ruiz et al. 2026), particularly Coombs's Situational Crisis Communication Theory (SCCT) (Claeys and Coombs 2019; Coombs 2007, 2018; Coombs and Holladay 1996, 2022; Coombs and Tachkova 2024), emphasize the alignment between crisis type, attributed responsibility, and response strategy (e.g., denial, diminishment, rebuilding, and bolstering). However, SCCT was originally developed with a largely one-way, organization-to-public communication model in mind. In networked digital environments, publics are not merely recipients of messages but active co-producers of crisis narratives (Vo et al. 2026). This calls for integrating crisis communication theory with network analytic approaches (Li et al. 2026) that account for user-driven amplification, clustering, and polarization.

Social network analysis in political and crisis communication. Social network analysis (SNA) (Staab and Thiel 2022; Durrheim and Schuld 2025) provides tools for examining the structural properties of online discourse, including degree centrality, betweenness centrality, network density, modularity, and community detection. Previous applications of SNA (Faustyna and Younus 2026) to political Twitter/X data (Golan and Himelboim 2016; Himelboim et al. 2014), such as Himelboim's work on network gatekeepers, have shown that political discourse networks often exhibit hub-and-spoke or star-like topologies, in which a small number of highly central accounts dominate the flow of information while peripheral communities remain loosely connected. Community detection algorithms such as Wakita–Tsurumi clustering (Wakita and Tsurumi 2007) further allow researchers to identify distinct opinion communities and to assess how information and narratives spread across cluster boundaries.

Research methodology

This study employed a mixed-methods design that combines quantitative social network analysis (SNA) (Reveilhac and Trembovelskyi 2025) with qualitative content analysis. It follows a sequential explanatory logic in which structural network patterns are first mapped and then interpreted through manual coding of the narrative strategy and stance of the underlying posts.

Data were collected using NodeXL Pro, a social network analysis add-in for Microsoft Excel that identifies and visualizes relationships among social media accounts. The dataset was constructed from X (Twitter) searches using the Indonesian keyword combination "Purbaya" AND

"Gubernur" ("governor"), limited to a maximum of 10,000 tweets. Data collection covered a 13-day period (October 1–14, 2025) and captured tweets, replies, mentions, retweets, and quote tweets referencing the search terms. The resulting network consists of 1,373 unique nodes (accounts) connected by 1,767 edges in total (1,596 unique edges and 171 duplicate edges), including 240 self-loops. All times in this article are reported in Western Indonesian Time (WIB, UTC+7). Because the Indonesian term "Gubernur" also retrieved posts about the Governor of Bank Indonesia, these posts were identified by keyword search ("Gubernur BI", "Bank Indonesia", "Perry") and checked manually (n = 135 edges generated by 28 original posts; 7.6% of all edges). On inspection, all of them concern allegations about Purbaya's earlier candidacy for Governor of Bank Indonesia (the claim that the seat was "priced" at Rp 900 billion), which circulated as part of the same controversy. They were therefore retained, and the reported metrics refer to the full network of 1,767 edges.

The network was visualized using the Harel–Koren Fast Multiscale layout algorithm, and node communities were identified using the Wakita–Tsurumi clustering algorithm, which groups accounts according to the relative density of their internal connections. The structural metrics analyzed included graph density, modularity, average geodesic distance, network diameter, and the distribution of connected components. To complement the structural analysis, a qualitative content analysis was conducted on the posts of each of the 14 main groups (G1–G14), focusing on narrative strategies and on the stance expressed by central and peripheral actors, as described below.

Content analysis procedure. Posts authored by accounts in clusters G1–G14 were coded, including retweets, which were coded according to the content of the retweeted post, giving a total of n = 1,531 coded posts (Table 4). Each post was coded for two variables. Narrative strategy had four categories: support/positive framing, clarification, criticism, and information sharing. Stance had three categories: supportive, critical, and neutral/moderate. Coding was carried out manually by the authors using a shared codebook (Supplementary Information 1); ambiguous cases were discussed until consensus was reached. No automated sentiment analysis tool was used; throughout this article, "sentiment" therefore refers to manually coded stance. The NodeXL data collection and analysis protocol, including all option settings, is provided as Supplementary Information 2.

Cluster labels. Wakita–Tsurumi clusters are structural communities, that is, groups of accounts that interact more densely with one another than with the rest of the network; they are not opinion groups. The labels supportive, critical and moderate were assigned to a cluster on the basis of its coded posts (a cluster was labelled supportive, critical or moderate according to the stance of the majority, i.e., more than 50%, of its coded posts, with the neutral/informational stance corresponding to the moderate label; in every cluster the dominant stance accounted for at least 71.8% of coded posts). The size, number of coded posts and dominant stance of each cluster are reported in Table 4.

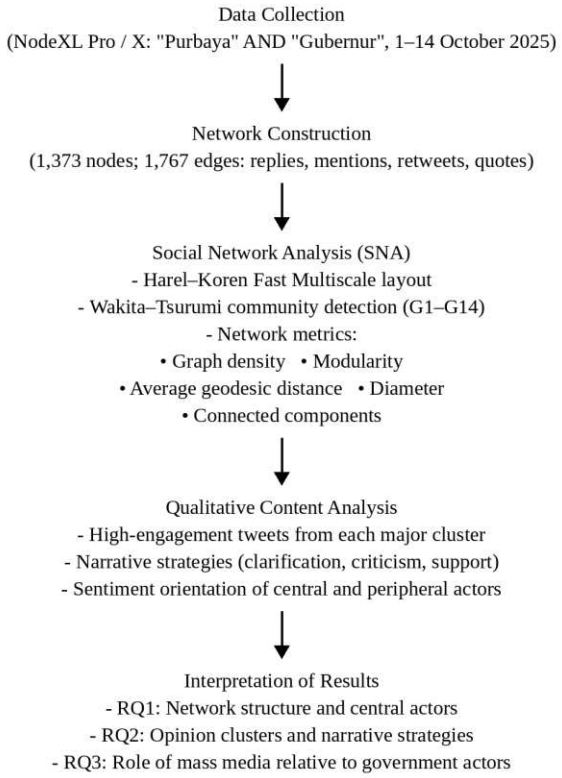


Fig. 2 Research method flow diagram (SNA of crisis communication on X). Source: compiled by the authors.

In Fig. 2, the flow of this research begins with the collection of digital data from X using NodeXL Pro with the keywords "Purbaya" AND "Gubernur". The collected interactions (replies, mentions, retweets, and quote tweets) are then constructed into a directed network of accounts and edges. Furthermore, SNA was carried out by visualizing the network with the Harel–Koren Fast Multiscale layout, identifying community clusters with the Wakita–Tsurumi algorithm, and calculating structural network metrics. The structural mapping is then complemented by a qualitative content analysis of the posts in each major cluster. The final stage is the interpretation of the results, in which the structural and narrative findings are linked to the three research questions concerning network structure and central actors, opinion clusters and narrative strategies, and the role of mass media relative to government actors.

Research results

The results show that the network on X concerning Purbaya Yudhi Sadewa is divided into 14 main structural clusters whose coded posts are predominantly supportive of the minister or neutral/informational in stance (Table 4). The largest cluster (G1, n = 504 accounts) contains only supportive posts and is built almost entirely on retweets of a single post. Of the 1,531 coded posts, 74.3% are supportive, 25.1% neutral or informational and only 0.6% (n = 9) critical; no cluster has a critical majority, so the anticipated polarization between supportive and critical groups did not materialize in this network. Supportive narratives rely mainly on ridiculing or discrediting the

governors and the national parliament, while neutral clusters circulate news reports. This study thus obtained the following findings that answer the research questions:

- Network structure and central actors (RQ1). The network is highly centralized: a private, non-verified influencer account (Influencer A; in-degree = 626; Table 3), through a single widely retweeted post, attracted 37.9% of all incoming ties, and the ten most central accounts together attracted 75.5%. The central accounts are private influencers and news outlets, not government actors; no account belonging to the minister appears in the network. Each major cluster is a star organized around one source account. Whether the central accounts also acted as opinion leaders or agenda-setters cannot be established from structural data alone.
- Opinion groups and narrative strategies (RQ2). Opinion is one-sided rather than polarized: eight of the 14 clusters are predominantly supportive of the minister and six are neutral/informational, while no cluster is critical. Supportive clusters combine positive framing of the minister with ridicule of the governors (e.g., as "helpless" or "checkmated") and allegations against the national parliament, spread almost entirely through retweets; hashtags play a minor role (3.1% of edges). Neutral clusters circulate news reports, and genuine dialogue is rare: replies and quotes make up 3.8% of edges and are concentrated in one small fact-checking cluster (G14).
- The role of mass media relative to government actors (RQ3). Mass media accounts are present but secondary: the highest-ranked media account, Kompas.com, is 5th by in-degree, with 59 incoming ties (Table 3), and the four most central outlets together attracted 10.5% of incoming ties, compared with 61.0% for the four leading influencer accounts. Each outlet anchors its own neutral/informational cluster (G6, G7, G10 and G11). Government accounts are almost absent: the Ministry of Finance account and the accounts of governors and provincial governments each received a single tie, and only one of them posted. These data do not allow conclusions about coordination through other channels.

Findings. Table 1 shows that the nodes (X accounts) in the graph were grouped into clusters based on their patterns of interaction with one another, such as mentioning, replying, retweeting, and quoting. This grouping was performed automatically using the Wakita–Tsurumi clustering algorithm, a community detection method that identifies parts of a network whose members are more densely connected to one another than to the rest of the network. In other words, nodes that interact with each other more frequently are assigned to the same cluster. This grouping facilitates analysis of the network structure and reveals the communities or discussion groups that formed around the search topic, in this case conversations on X related to the keywords "Purbaya" and "Gubernur".

Table 1 NodeXL graph metrics for the "Purbaya" AND "Gubernur" network.

Graph metric	Value
Graph type	Directed
Vertices	1373

Graph metric	Value
Unique edges	1596
Edges with duplicates	171
Total edges	1767
Self-loops	240
Reciprocated vertex pair ratio	0.001328904
Reciprocated edge ratio	0.00265428
Connected components	126
Single-vertex connected components	99
Maximum vertices in a connected component	1201
Maximum edges in a connected component	1553
Maximum geodesic distance (diameter)	11
Average geodesic distance	3.53476
Graph density	0.000799997
Modularity	0.639027
NodeXL version	1.0.1.553
Graph gallery URL	Not available
Graph image URL	Not available
Graph source	Twitter Search3
Graph term	"Purbaya" AND "Gubernur"
Data import description	The graph represents a network of 1,373 Twitter users whose recent tweets contained "Purbaya" AND "Gubernur", or who were replied to, mentioned, retweeted, or quoted in those tweets, taken from a data set limited to a maximum of 10,000 tweets posted between 01/10/2025 00:00:00 and 14/10/2025 11:16:47. The network was obtained from Twitter on Tuesday, October 14, 2025 at 12:19 WIB (05:19 UTC). The tweets in the network were posted over the 13-day, 0-hour, 43-minute period from Wednesday, October 1, 2025 at 11:35 WIB to Tuesday, October 14, 2025 at 12:19 WIB. There is an edge for each "replies-to" relationship in a tweet, an edge for each "mentions" relationship in a tweet, an edge for each "retweet" relationship, an edge for each "quote" relationship, an edge for each "mention in retweet" relationship, an edge for each "mention in reply-to" relationship, an edge for each "mention in quote" relationship, an edge for each "mention in quote reply-to" relationship, and a self-loop edge for each tweet that is not a replies-to, mentions, retweet, or quote.
Layout algorithm	The graph is laid out using the Harel–Koren Fast Multiscale layout algorithm.
Grouping	Graph vertices are grouped by cluster using the Wakita–Tsurumi clustering algorithm.

Source: data processing using NodeXL Pro.

Figure 3 presents a vertical bar chart of the frequency with which particular tweets, words, phrases, and accounts appear in the X network constructed from the keyword search "Purbaya" AND "Gubernur". The horizontal axis displays the most frequently occurring items (e.g., "Itu DPR

bertanya...", @hustrio, RT, polemic, and Purbaya), and the vertical axis shows their frequency of occurrence or engagement in the network collected and analyzed with NodeXL. Retweets (RT) dominate the chart: several entries are retweets, the most frequent of which approaches 600 occurrences, indicating that most activity in the network consists of redistributing other users' tweets. Accounts such as @hustrio, @PartaiSocmed, and @xLanglangBuana appear with moderate frequency, whereas terms such as Purbaya, governor, polemic, minister, and Minister of Finance, as well as shortened links (https://t.co/), appear considerably less often than "RT". Several items are fragments of tweets or frequently discussed topics, reflecting the noise typical of social media text (e.g., sentence fragments and URLs). Overall, the chart indicates that retweeting is the dominant form of interaction in this network and that information spread virally through redistribution rather than through two-way discussion, which would typically appear as replies or mentions.

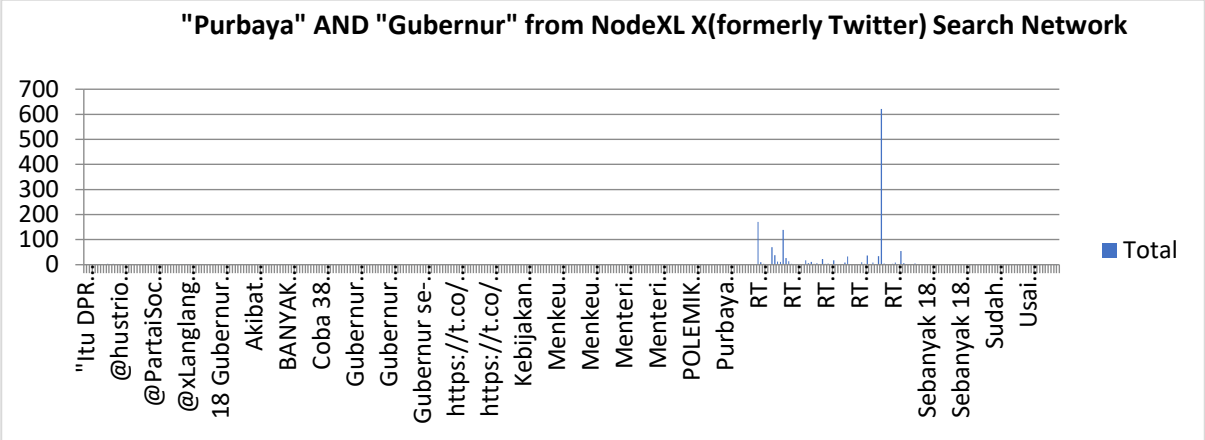


Fig. 3 Frequency of the most frequently occurring items in the "Purbaya" AND "Gubernur" X (formerly Twitter) search network. Source: data processing using NodeXL Pro.

Figure 4 shows the number of tweets (count of tweets) containing specific words, phrases, accounts, or entities in the X network retrieved with the keywords "Purbaya" and "Gubernur" using NodeXL. The horizontal axis displays frequently occurring items, including accounts (e.g., @Jokowi, @PartaiSocmed, and @DedekChaniago), words and phrases (e.g., "Itu DPR bertanya..." ["The House of Representatives asked..."], Governor of DKI Jakarta, Minister of Finance, consequences, RT, and polemic), and shortened URLs (https://t.co/...), which indicate links embedded in tweets. The vertical axis shows the number of tweets mentioning each item, on a scale of up to 700. Retweets again dominate, with one "RT" entry exceeding 600 tweets, making retweeting the most common form of interaction and reflecting the high level of diffusion typical of viral topics. Accounts such as @Jokowi, @PartaiSocmed, and @mediaindonesia appear relatively often, and phrases such as "Minister of Finance", "Governor of DKI Jakarta", and "Purbaya polemic" link the conversation to political and governmental issues. Words such as "effect", "already", "after", "response", and "budget" suggest statements and discourse developing around Purbaya and the role of the governors. Taken together, the dominance of retweets indicates that narratives and news about Purbaya and the governors spread massively through redistribution

rather than direct conversation; the presence of accounts such as @Jokowi and @mediaindonesia signals national political relevance and mainstream media attention; terms such as "Minister of Finance", "polemic", and "budget" place the conversation in the context of fiscal policy and public debate on government statements; and the frequent URLs indicate that many tweets linked to news articles or other external sources.

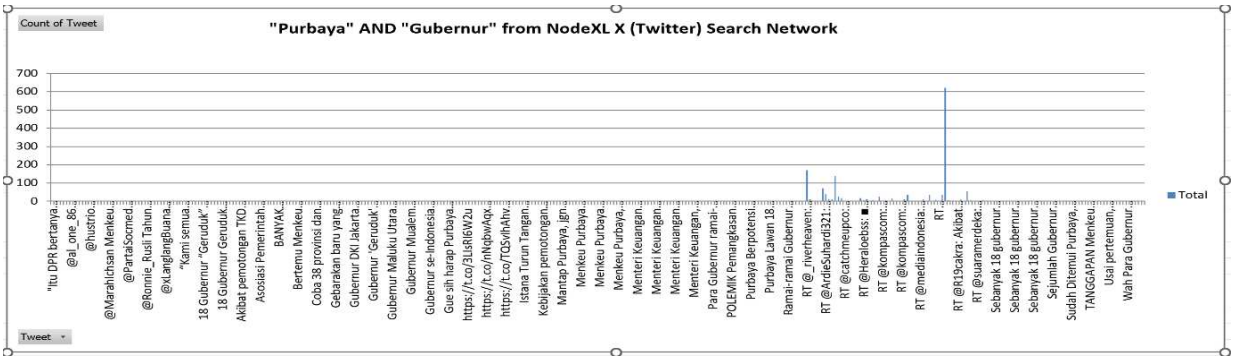
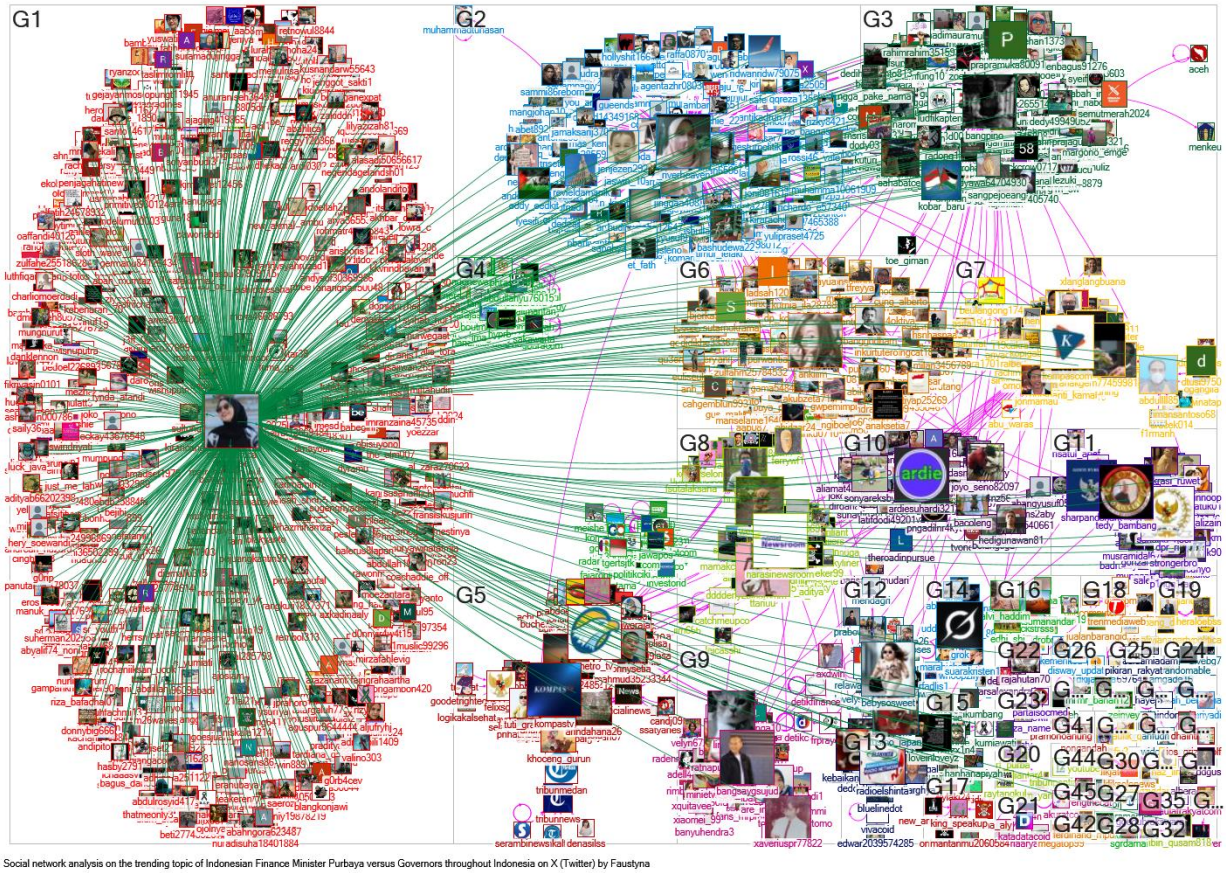


Fig. 4 Tweet counts for frequently occurring words, phrases, and accounts in the "Purbaya" AND "Gubernur" X (Twitter) search network. Source: data processing using NodeXL Pro.

Figure 5 presents the NodeXL visualization of interactions on X related to "Purbaya" and "Gubernur" in Indonesia, including retweets, mentions, replies, and quote tweets. Each node (shown as a profile thumbnail) represents one X account, and each edge (line or arrow) represents an interaction between accounts. NodeXL groups accounts that interact with one another into clusters labeled G1, G2, G3, and so on. G1 is the largest group (504 accounts). It contains a single dominant account, Influencer A, which receives a large number of incoming edges; almost all of G1's edges (99%) are retweets of one post by this account, making it the main channel of information diffusion in the network. G2, G3 and G5 have the same star structure on a smaller scale, each organized around retweets of a post by another influencer account (Influencers B, C and D; Table 3). G6, G7, G10 and G11 are organized around news outlets (Kompas.com, Kompas TV, Metro TV and Narasi Newsroom), whose reports are retweeted by their followers. G4 consists of stand-alone posts that do not interact with other accounts, and G14 is a small cluster of reply threads. In the visualization, node color indicates cluster membership, node (profile picture) size is proportional to betweenness centrality, edge colour is uniform (NodeXL default) and does not represent relationship type or edge weight, and the G# labels are assigned automatically by the Wakita–Tsurumi clustering algorithm. Overall, the conversation about "Purbaya" and "Gubernur" is strongly centered on one influencer account in G1, whereas the other groups form smaller stars around other influencers or news outlets. The network thus has a hub-and-spoke structure, and interactions take the form of retweets rather than two-way debate.



Social network analysis on the trending topic of Indonesian Finance Minister Purbaya versus Governors throughout Indonesia on X (Twitter) by Faustyna

Fig. 5 NodeXL network graph of X (Twitter) interactions on "Purbaya" and "Gubernur" in Indonesia, grouped into clusters G1–G14. Source: data processing using NodeXL Pro.

Figure 6 presents the SNA visualization as an ego network centered on Influencer A, the account with the highest in-degree in the network (Table 3). The network was visualized with NodeXL, which divided it into groups G1–G14 shown in different community colors. The visualization reveals a very strong hub-and-spoke (star) structure, with a large share of communication ties converging on this single account at the center of the network. The account is a private, non-verified account with about 102,600 followers that describes itself as a "critic"; it is neither a government nor a media account. Its position rests on one post, published on 10 October 2025 at 00:23 WIB, which framed the governors as "helpless" and "checkmated" by the minister and quoted him contrasting regional spending on festivals with spending on irrigation repair. This post was retweeted 621 times over the following four days, so that the account alone attracted 37.9% of all incoming ties in the network (in-degree = 626; Table 3). In SNA terms, it occupies the structural position of an information hub connecting several communities; whether it also acted as an opinion leader or agenda-setter cannot be established from structural data alone. Because almost all of its ties are retweets, the account functioned as a source of amplified content rather than as a site of discussion: users redistributed its framing of the dispute rather than responding to it. In crisis communication terms, the minister's side of the controversy was thus visibly represented on X by a third-party account rather than by the minister or his ministry.

The network is nevertheless fragmented into 14 main communities (G1–G14), indicating that the conversation did not take place within a single homogeneous group. Four of the five largest clusters (G1, G2, G3 and G5) are each organized around a post by a private influencer account, four mid-sized clusters (G6, G7, G10 and G11) around news outlets, and two smaller clusters (G8 and G12) around posts alleging that the minister's earlier bid to become Governor of Bank Indonesia failed because members of the national parliament had "priced" the seat at Rp 900 billion. Inter-cluster ties are few (229 edges, 13.0% of all edges) and come mainly from accounts that retweeted posts by more than one influencer, most often linking G2, G3 and G5 to G1. Several media accounts, such as Kompas, Tribun, Metro TV and various local outlets, are present in the network but are not located at its center (the highest-ranked media account, Kompas.com, is 5th by in-degree, with 59 incoming ties; Table 3). The media therefore appear to function mainly as secondary hubs for informational content rather than as the primary sources of the dominant narratives. Accounts of the Ministry of Finance, of governors and of provincial governments also appear, but each received a single tie (Fig. 10). Government accounts therefore did not form a visible network on X during the observed period; these data do not allow conclusions about coordination through other channels. Finally, network density is low (0.0008; Table 2): there are many nodes, many edges converge on a few source accounts, and there is little cross-linking between communities. Information therefore flows from a few sources to many redistributors; it spreads quickly, but the scope for public deliberation is relatively limited.

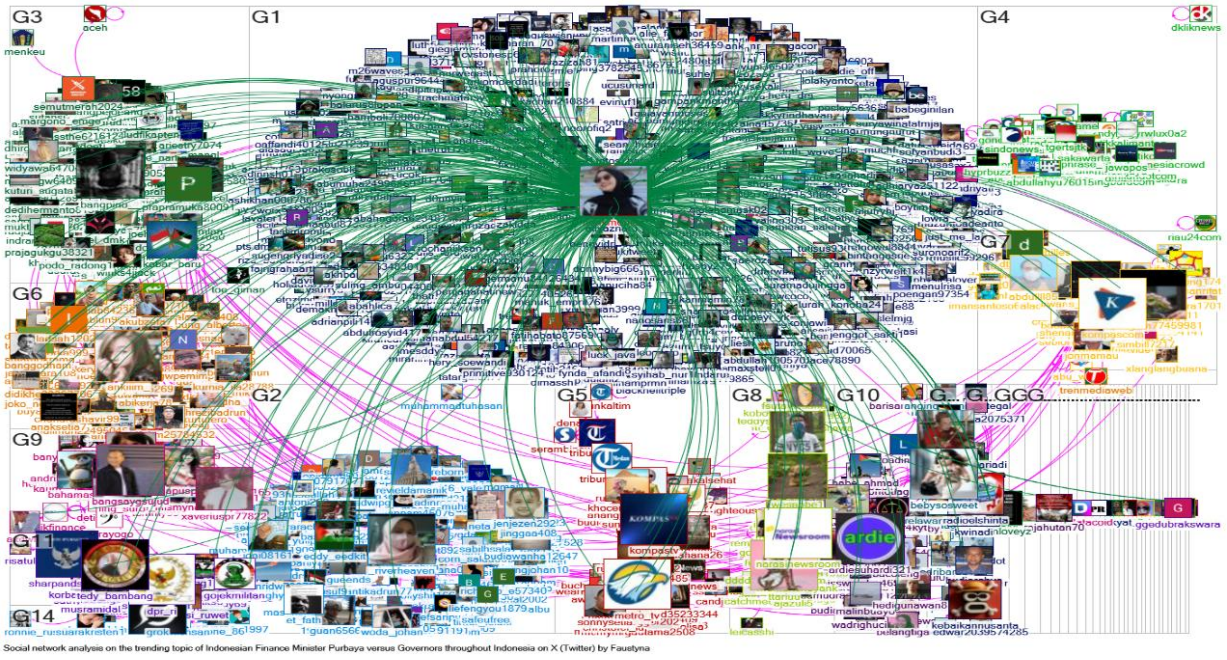


Fig. 6 Ego network of X (Twitter) interactions centered on Influencer A, the most central account in the "Purbaya" AND "Gubernur" network. Source: data processing using NodeXL Pro.

Figure 7 visualizes the digital communication structure that formed on X in public conversations about Indonesia's Minister of Finance, Purbaya Yudhi Sadewa, and his dispute with regional governors. The NodeXL Pro analysis produced 14 main groups (G1–G14) based on the

modularity-based clustering algorithm. G1 is the largest group and the center of the conversation, but it is also among the sparsest (density 0.002; Fig. 8), because it consists almost entirely of accounts retweeting one post. The accounts with the highest betweenness centrality (Table 3) are the source accounts of the main clusters, and their brokerage position derives from being retweeted by users who also retweeted other sources. Edges between clusters show where content crossed community boundaries: the largest inter-cluster flows link G3 (32 edges), G5 (21) and G2 (13) to G1, so the other influencer clusters are those most closely connected to G1. Because edge colour was not mapped to edge weight, it does not indicate the strength of these ties. Combined with the coded stance of each cluster (Table 4), the structure does not show polarization between supporters and critics of the minister; instead, it shows segmentation between supportive clusters built around influencer posts and neutral clusters built around news reports. In this case, the network is centralized around a dominant hub yet divided into loosely connected communities.

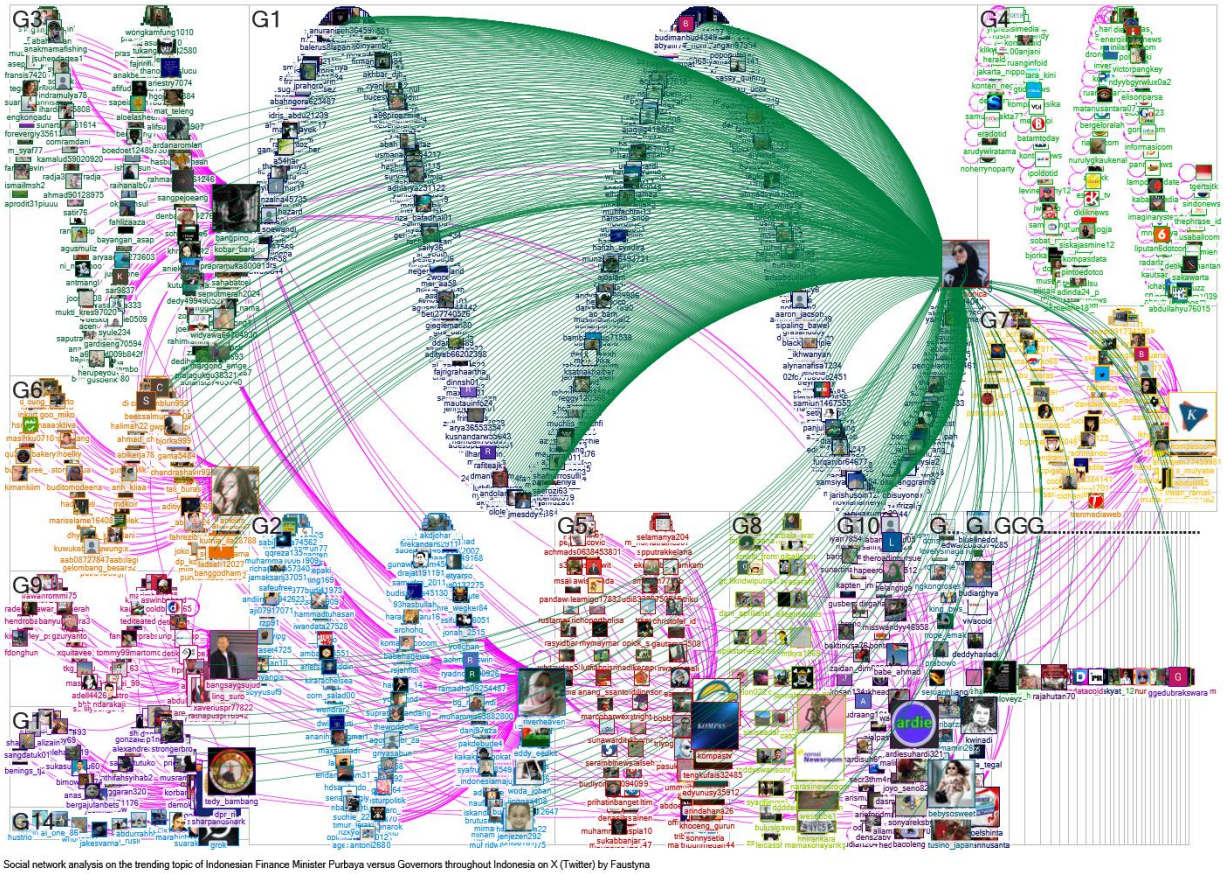


Fig. 7 Inter-cluster connections in the X (Twitter) network on "Purbaya" and "Gubernur" in Indonesia. Source: data processing using NodeXL Pro.

Network structure overview. The resulting network is directed and consists of 1,373 nodes and 1,767 edges (Table 2). At the macro level, it is highly fragmented, containing 126 connected components, 99 of which are single-node (isolated) components. However, most accounts (1,201 nodes, 87.5% of the network) belong to a single largest connected component containing 1,553 edges, indicating that most participants in the discourse are structurally connected, directly or

indirectly. The network has a maximum geodesic distance (diameter) of 11 and an average geodesic distance of 3.53, suggesting that information can travel across the network relatively efficiently despite its size. Graph density is very low (0.0008), a pattern typical of large-scale, loosely connected social media discourse networks rather than densely interconnected communities. The relatively high modularity (0.639) indicates that the network is organized into well-defined, internally cohesive communities.

Table 2 Key network metrics.

Network metrics	Value
Graph type	Directed
Nodes (unique accounts)	1,373
Unique edges	1,596
Duplicate edges	171
Total edges	1,767
Self-loops	240
Reciprocated node pair ratio	0.0013
Reciprocated edge ratio	0.0027
Connected components	126
Single node components	99
Largest component (nodes)	1,201
Largest component (edges)	1,553
Maximum geodesic distance (diameter)	11
Average geodesic distance	3.53
Graph density	0.0008
Modularity	0.639

Source: data processing using NodeXL Pro.

Centralization and hub-and-spoke patterns. Visual and structural analysis reveals a clear hub-and-spoke (star-like) topology in which communication is highly concentrated around a small number of source accounts. The most central account, Influencer A, is a private influencer account rather than an account of the government official at the center of the controversy. It exhibits disproportionately high in-degree centrality (in-degree = 626; Table 3), attracting 37.9% of all incoming ties in the network, almost entirely as retweets of one post. The four leading influencer accounts together attracted 61.0% of incoming ties, and the ten most central accounts 75.5%. In SNA terms, these accounts occupy the structural position of information hubs and bridges between otherwise weakly connected communities; whether they also acted as opinion leaders or agenda-setters cannot be established from structural data alone. Horizontal connections among peripheral users remain sparse: the reciprocated edge ratio is 0.0027 (Table 2), and replies and quotes make up only 3.8% of edges. This pattern suggests that visible communication during the crisis was source-centered rather than community-driven, but the sources were third-party influencers rather

than the authorities involved. Because these ties are mostly retweets, they show which content was amplified, not that the source accounts were trusted.

Table 3 The 10 most central accounts in the network, ranked by in-degree centrality.

1	Influencer A	Private account	626	1	1,115,300.6	0.4359	0.6985	0.0535	G1	102,559
2	Influencer B	Private account	171	1	336,021.6	0.3116	0.0330	0.0143	G2	47,809
3	Influencer C	Private account	140	1	238,354.3	0.3013	0.0560	0.0104	G3	36,110
4	Influencer D	Private account	70	1	106,296.3	0.2830	0.0302	0.0054	G5	10,015
5	@kompascom	News media	59	1	103,527.7	0.2806	0.0142	0.0048	G6	8,801,299
6	@metro_tv	News media	42	1	68,358.0	0.2803	0.0100	0.0036	G10	10,936,877
7	User E	Private account	38	2	58,717.7	0.2753	0.0105	0.0030	G8	2,880
8	@kompastv	News media	37	1	83,345.7	0.2746	0.0064	0.0033	G7	5,620,980
9	@narasinewsroom	News media	35	1	66,895.5	0.2643	0.0072	0.0032	G11	332,839
10	@dpr_ri	State institution	29	0	33,368.9	0.2660	0.0099	0.0017	G12	485,333

Accounts of private individuals are pseudonymised (Influencers A–D, User E); accounts of media organisations and state institutions are retained. Source: data processing using NodeXL Pro.

Community structure and cluster roles. Community detection identified 14 main clusters (G1–G14), which together contain 1,244 of the 1,373 accounts; the remaining accounts form many very small groups. The clusters fall into four types (Fig. 8). Influencer clusters (G1, G2, G3, G5, G9 and G13) are stars in which 32–99% of the cluster's outgoing ties are retweets of a single post by a private account; all are predominantly supportive of the minister. Allegation clusters (G8 and G12) are organized around posts claiming that the minister's earlier bid to become Governor of Bank Indonesia failed because the seat had been "priced" at Rp 900 billion; they are also supportive, directing criticism at the national parliament rather than at the minister. Media clusters (G6, G7, G10 and G11) are organized around news outlets and are predominantly neutral/informational. Finally, G4 consists of stand-alone posts, many of them by news portals, and G14 of reply threads in which users and an AI chatbot checked the Rp 900 billion claim; both are neutral. G1 is the largest cluster but also among the sparsest (density 0.002), whereas density is highest in the small reply-based cluster G14 (0.083). Table 4 reports the size, coded posts and dominant stance of each cluster, and Fig. 8 summarizes the resulting typology of cluster roles.

Table 4 Size, coded posts and dominant stance of clusters G1–G14.

Cluster	Nodes	Edges	Coded posts (n)	Pro-Purbaya	Neutral	Critical	Dominant stance	Retweet edges (n)
G1	504	505	505	505	0	0	Pro-Purbaya (100.0%)	502
G2	139	141	154	152	2	0	Pro-Purbaya (98.7%)	139
G3	118	118	165	165	0	0	Pro-Purbaya (100.0%)	116
G4	99	136	123	14	104	5	Neutral/informational (84.6%)	0
G5	64	63	97	97	0	0	Pro-Purbaya (100.0%)	63
G6	53	71	80	10	69	1	Neutral/informational (86.2%)	56
G7	46	67	82	7	72	3	Neutral/informational (87.8%)	40
G8	43	51	71	58	13	0	Pro-Purbaya (81.7%)	46
G9	42	63	71	51	20	0	Pro-Purbaya (71.8%)	47
G10	39	42	60	13	47	0	Neutral/informational (78.3%)	36
G11	36	37	49	8	41	0	Neutral/informational (83.7%)	35
G12	28	53	38	37	1	0	Pro-Purbaya (97.4%)	26
G13	17	17	18	17	1	0	Pro-Purbaya (94.4%)	13
G14	16	27	18	3	15	0	Neutral/informational (83.3%)	3

Dominant stance assigned according to the rule described in "Research methodology". Source: data processing using NodeXL Pro and the authors' content analysis.

Cluster	Nodes / edges	Density	Anchor account	Anchor share*	Dominant stance	Main content of anchor post(s)
G1	504 / 505	0.002	Influencer A	99%	Supportive (100%)	Governors 'helpless', 'checkmated' by the minister
G2	139 / 141	0.007	Influencer B	90%	Supportive (98.7%)	'Fiscal gladiator arena': minister vs 18 governors
G3	118 / 118	0.009	Influencer C	70%	Supportive (100%)	Old minister 'hated by the people', new one 'by officials'
G4	99 / 136	0.000	None (standalone posts)	0%	Neutral (84.6%)	Stand-alone news posts on the governors' protest
G5	64 / 63	0.016	Influencer D	65%	Supportive (100%)	Joke about the minister's earlier failed bid; jab at DPR
G6	53 / 71	0.020	@kompascom (media)	57%	Neutral (86.2%)	News quoting the minister on revenue-sharing cuts
G7	46 / 67	0.022	@kompastv (media)	40%	Neutral (87.8%)	News: governor's donation drive and minister's reply
G8	43 / 51	0.026	User E	49%	Supportive (81.7%)	Claim that the BI governor seat was 'priced' at Rp 900 bn
G9	42 / 63	0.027	Influencer F	32%	Supportive (71.8%)	Minister approves a vital bridge for a province
G10	39 / 42	0.026	@metro_tv (media)	59%	Neutral (78.3%)	News: 18 governors visit the minister's office
G11	36 / 37	0.028	@narasinewsroom (media)	65%	Neutral (83.7%)	News: governors' association meets the minister

Fig. 8 Typology of cluster roles (G1–G14): size, density, anchor account, anchor share, dominant stance and main content of the anchor post(s). Private accounts are pseudonymised. Source: data processing using NodeXL Pro and the authors' content analysis.

The role of mass media accounts. Several verified mass media accounts (e.g., national news outlets and major broadcasters) are present in the network but do not occupy the most central positions (Table 3). The four most central outlets (Kompas.com, Metro TV, Kompas TV and Narasi Newsroom) together attracted 10.5% of incoming ties, compared with 61.0% for the four leading influencer accounts (Fig. 9). Each outlet anchors its own cluster in which users retweet its reports, and these clusters are predominantly neutral/informational. The media thus act as secondary hubs that supply factual reporting on the dispute, including the minister's own statements, while the evaluative framing that dominated the network came from influencer accounts. Because this study examines a single episode, it cannot show a change over time in the gatekeeping role of the mass media.

Figure 9 compares the in-degree of the ten most central accounts with that of the government accounts that appear in the network, by account type. Private influencer accounts dominate, news outlets form a second tier, and state institutions and officials are marginal: apart from the national parliament account, which was mentioned in retweets of the Rp 900 billion allegation, each government account received a single incoming tie. In this network, users therefore encountered the controversy mainly through influencer posts and, to a lesser extent, through news reports, rather than through the official channels of the parties to the dispute.

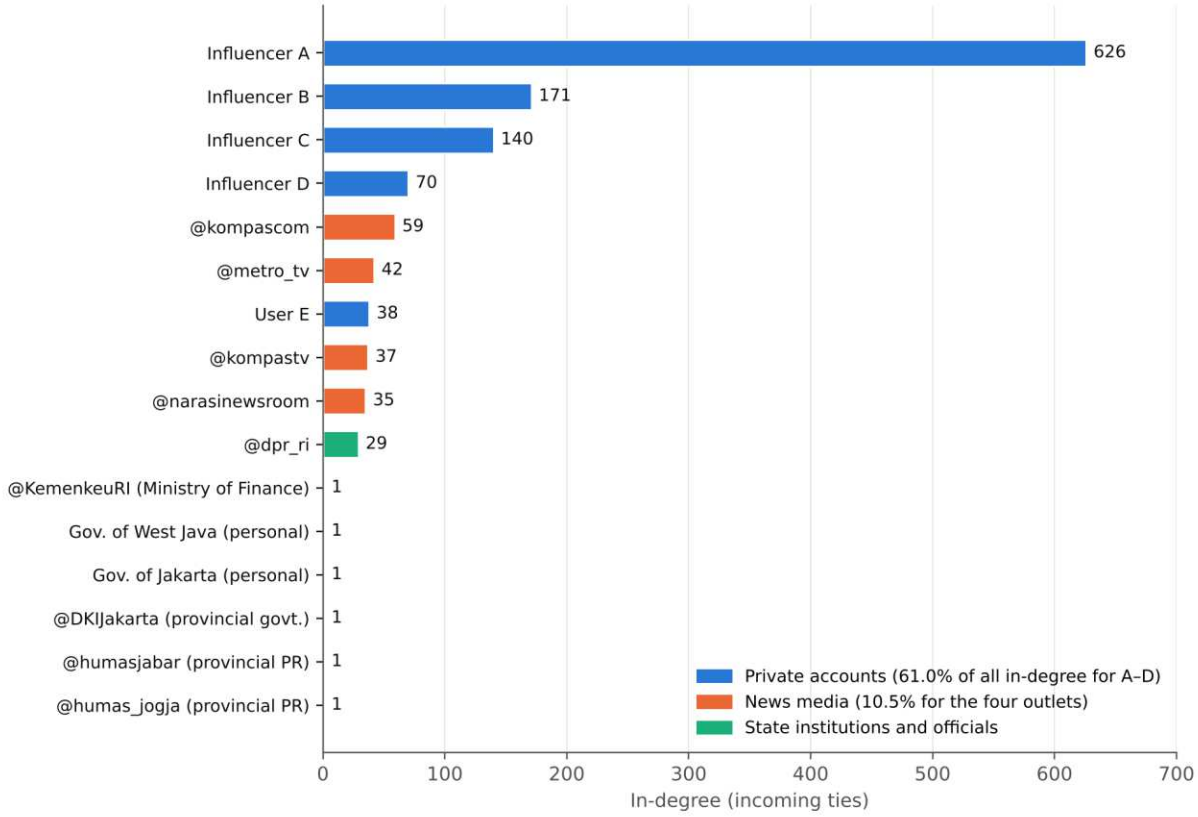


Fig. 9 In-degree of the ten most central accounts and of government accounts, by account type. Private accounts are pseudonymised. Source: data processing using NodeXL Pro.

Government accounts. Accounts representing the parties to the dispute are almost absent from the network (Fig. 10). No account of the Minister of Finance appears; the Ministry of Finance account, the personal accounts of the governors of West Java and Jakarta, and the accounts of the Jakarta, West Java and Yogyakarta provincial governments each received a single incoming tie. Most sit in very small peripheral groups of two to four accounts; the Yogyakarta account, the only one that posted during the observation window, appears in G4 because of a single stand-alone post. Government accounts therefore did not form a visible sub-network on X and did not engage in the discussion; the governors' position reached the network mainly through news reports of their protest rather than through their own accounts. These data do not allow conclusions about

coordination through other channels. Figure 10 lists these accounts with their cluster, in-degree, number of posts and the way they entered the network.

Account	Role	Cluster (size)	In-degree	Posts	How the account entered the network
@KemenkeuRI	Ministry of Finance	G40 (2)	1	0	Mentioned in one quote post
Governor of West Java	Governor (personal account)	G25 (4)	1	0	Mentioned in one reply
@humasjabar	West Java provincial PR	G25 (4)	1	0	Mentioned in the same reply
Governor of Jakarta	Governor (personal account)	G33 (2)	1	0	Mentioned in one post
@DKIJakarta	Jakarta provincial government	G28 (3)	1	0	Mentioned in one news post
@humas_jogja	Yogyakarta provincial PR	G4 (99)	1	1	One stand-alone post (self-loop)
@dpr_ri	House of Representatives	G12 (28)	29	0	Mentioned in retweets of the Rp 900 bn claim

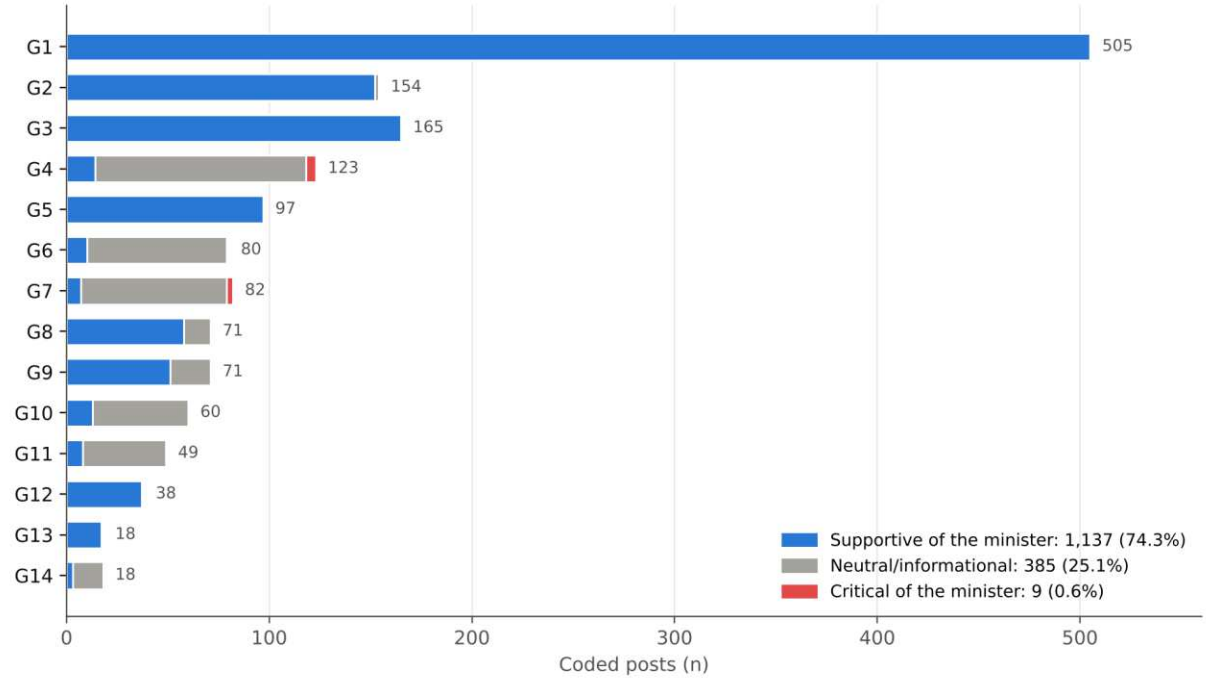
No account of the Minister of Finance appears in the network. 'Posts' = out-degree (interactions initiated by the account).

Fig. 10 Government accounts in the network: cluster (size), in-degree, posts and how each account entered the network. Source: data processing using NodeXL Pro.

One-sided opinion and narrative strategies. Qualitative content analysis of n = 1,531 coded posts shows that opinion in this network was one-sided rather than polarized (Fig. 11a). Of the coded posts, 1,137 (74.3%) were supportive of the minister, 385 (25.1%) were neutral or informational, and only 9 (0.6%) were critical; no cluster had a critical majority. Supportive posts rely on two strategies. The first is positive framing of the minister as firm and fiscally responsible, for example as someone who "sees what the public does not see" and approves vital infrastructure while rejecting wasteful spending. The second, and more widely amplified, is to discredit the other side of the dispute: the governors are portrayed as "helpless", "checkmated" or "shouting loudest when it comes to money", and the national parliament is accused of having "sold" the Bank Indonesia governor seat. Clarification of the policy itself appears mainly in news reports, which form the neutral clusters. These narratives spread almost entirely through retweets (79.6% of edges; Fig. 11b), whereas hashtags were rare (3.1% of edges) and reply-based exchange was confined to a small cluster (G14) in which users fact-checked the Rp 900 billion claim.

Figure 11 summarizes the content analysis. Panel a shows the coded stance of each cluster: supportive posts dominate the influencer and allegation clusters, neutral posts dominate the media clusters and the stand-alone and reply clusters, and critical posts are almost absent. Panel b shows the distribution of interaction types: retweets account for 79.6% of all edges, whereas replies, mentions in replies and quotes together account for 3.8%. Together, the two panels indicate that the dominant pro-minister framing was amplified through redistribution rather than negotiated through dialogue.

a



b

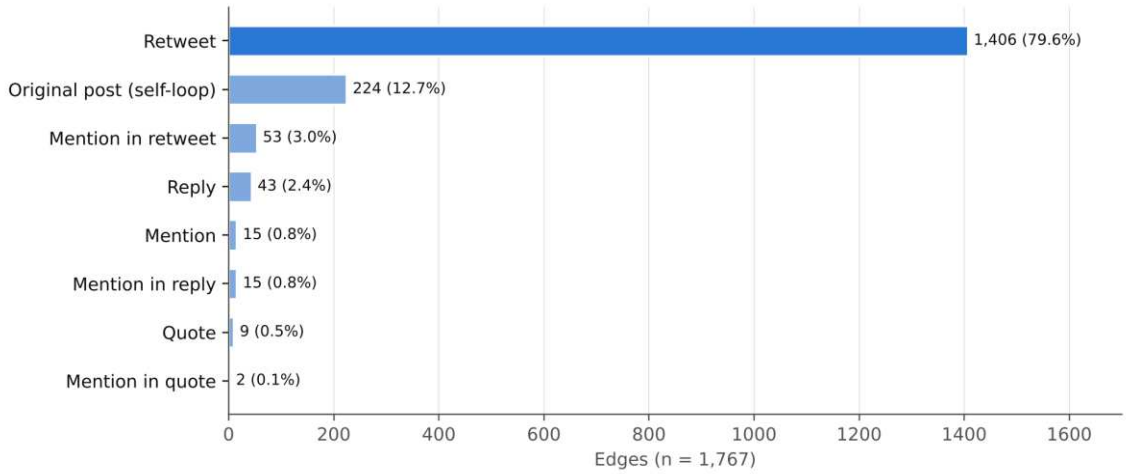


Fig. 11 Stance and interaction types. a Coded stance by cluster (n = 1,531 posts). b Interaction types across all edges (n = 1,767). Source: data processing using NodeXL Pro and the authors' content analysis.

Discussion

This study analyzes the structure of the opinion network that formed on X during the controversy between Indonesia's Minister of Finance and regional governors using NodeXL, focusing on the position of central actors, the narrative strategies of opinion groups, and the role of mass media in shaping public opinion during the crisis. The researchers analyzed:

- Influencer-centered rather than authority-centered crisis communication: the network has a highly centralized hub-and-spoke structure, but its hub is a private influencer account rather

than a government account, so that visible communication about the official's crisis converged on third-party amplifiers rather than on the authorities involved or on peer-to-peer deliberation.

- Media as secondary hubs: mass media accounts are present but secondary, anchoring neutral clusters that circulate news reports, while the evaluative framing of the dispute came mainly from influencer accounts.
- One-sided opinion rather than polarization: supportive posts dominate and critical posts are almost absent; supporters defended the minister mainly by discrediting the governors and the national parliament, and dialogue was rare and confined to a small fact-checking cluster.

The hub-and-spoke structure identified in this study suggests that crisis communication in this case was centralized, but not around the authorities involved. This is consistent with previous SNA research on political Twitter networks, which frequently identifies centralized, star-like topologies in which a few highly retweeted accounts dominate the flow of information (Himelboim et al. 2014; Recuero et al. 2019). What distinguishes this case is the identity of the hub. Neither the minister nor the ministry, nor the governors who challenged him, occupied a central position; the dominant hub was a private influencer account, and the next most central accounts were other influencers and news outlets. Himelboim et al. (2014) describe such accounts as social mediators that shape how organizational messages reach publics. Here, they did more than relay messages: they enacted crisis response strategies on the minister's behalf, combining bolstering of the minister with what SCCT describes as attacking the accuser (Coombs 2007), directed at the governors and at the national parliament. These findings suggest a possible extension of Situational Crisis Communication Theory (Coombs 2007; Jong 2025): in a networked environment, crisis response strategies may be enacted by third-party accounts that the organization does not control, and the structural position of these accounts, and not only the content of their messages, may matter for how a crisis is framed. This proposition requires testing across further cases.

The secondary structural position of mass media accounts is consistent with the argument that networked communication reconfigures the traditional gatekeeping function of journalism during political crises (Bastos et al. 2013; Reveilhac and Trembovelskyi 2025). In this case, however, the actors who bypassed the media were not the officials themselves but influencer accounts, which framed the dispute in evaluative terms while news outlets supplied factual reports, including the minister's own statements. This may have implications for crisis management practice: when official accounts are absent from the conversation, the framing of an official's crisis may be shaped largely by third parties whose aims and accuracy the institution cannot control, as illustrated by the circulation of an unverified allegation about the minister's earlier candidacy.

The near absence of critical posts should be interpreted with care. It may partly reflect the query, which captured posts mentioning both the minister and the governors, and the fact that the governors' own accounts did not engage, so that their position was voiced mainly through news reports. Nonetheless, the pattern is in line with the broader literature on networked publics, which shows that digital crisis discourse comprises structurally distinct sub-publics with different modes

of engagement (Durrheim and Schuld 2025; Recuero et al. 2019). Here, the sub-publics differed less in their stance toward the minister than in their source of information: influencer posts versus news reports. The small fact-checking cluster (G14) shows that verification can emerge spontaneously, but at a scale far smaller than the amplification of the original claims. For crisis communication practitioners, this suggests that monitoring which third-party accounts are framing an issue, and engaging with the information-oriented news clusters, may be as important as issuing official statements.

Limitations. Several limitations should be considered when interpreting these findings. First, the study is based on a single case and a 13-day observation window (1–14 October 2025). The patterns identified describe this episode and cannot be generalised to other crises, officials or periods, nor do they capture how the network evolved across the full crisis lifecycle. Second, the data come from one platform (X) and from NodeXL's search import, which is capped at 10,000 posts and relies on the platform's search interface; the dataset is therefore a sample of the conversation rather than a complete record, and posts that were deleted, protected or published outside the query window are not included. Third, the query "Purbaya" AND "Gubernur" may both over- and under-include relevant content: the term "Gubernur" also captured posts about the Governor of Bank Indonesia (n = 135 edges, 7.6% of all edges; on inspection these concerned allegations about Purbaya's own earlier candidacy for that post and were therefore retained), while posts referring to the controversy with other terms (e.g., "Menkeu", "TKD" or hashtags without both keywords) were missed. Fourth, automated or coordinated accounts were not systematically detected, so part of the retweet volume, particularly in the influencer clusters, may reflect bot or coordinated activity rather than organic public opinion. Fifth, Wakita–Tsurumi clusters are structural communities; labelling them as supportive or neutral relies on manual coding of posts authored by cluster members (n = 1,531), most of which are retweets, so stance was inferred largely from amplified content and may not reflect the views of all cluster members; moreover, coding was done by consensus and no formal intercoder reliability statistic was computed. Sixth, structural centrality does not by itself indicate trust, credibility or influence: the high in-degree of the central account reflects the amplification of one post, not necessarily agreement with it, trust in its author or reliance on it as an information source, and the positions of media and governor accounts describe visible interaction on X only, not offline or institutional coordination. Finally, the analysis is descriptive and cross-sectional. It does not measure changes in public opinion or test causal relationships, so statements about how network structure relates to opinion should be read as associations to be tested in future longitudinal, multi-platform studies using inferential network models (e.g., exponential random graph models).

Conclusion

This study suggests that, in the case examined, crisis communication on X was closely associated with the structural properties of the interaction network. The case reveals a highly centralized hub-and-spoke structure, but the dominant hub was a private influencer account rather than a

government actor, and the parties to the dispute (the minister, his ministry and the governors) were almost absent from the network. Opinion was one-sided rather than polarized: supportive posts dominated, critical posts were almost absent, and supporters defended the minister mainly by discrediting the governors and the national parliament. Mass media accounts served as secondary hubs that supplied informational content, while the evaluative framing of the dispute came from influencer accounts, a pattern that should be examined in further cases. Theoretically, the study offers an exploratory extension of Situational Crisis Communication Theory, illustrating how crisis response strategies can be enacted by third-party accounts and how network-structural variables (centralization, modularity, and community structure) can be integrated with the analysis of narrative strategy and coded stance.

To address the limitations set out in the "Limitations" subsection, future research should examine cross-platform crisis communication dynamics, adopt longitudinal designs to track network evolution across the crisis lifecycle, and incorporate inferential statistical modeling (e.g., exponential random graph models) to test how the structural position of third-party accounts relates to the framing and stance of crisis discourse.

Implications and recommendations. The results of this study suggest that the structure of the network, and not only the content of messages, may matter for how crisis information circulates in the digital public sphere. Practically, the findings suggest that crisis communication practitioners should invest in social network analytics capabilities to identify central actors, including third-party influencers, as well as bridging and information-oriented clusters in real time, enabling more targeted and adaptive crisis response strategies. Based on these findings, and within the limits of a single case, several tentative recommendations can be made. First, government institutions involved in a public dispute should be visibly present on X with timely, verifiable information, because in their absence the framing of the dispute is likely to be set by third-party accounts. Second, communicators should monitor and, where necessary, respond to unverified claims amplified by influencer accounts, such as the Rp 900 billion allegation observed here, and support the information-oriented clusters formed around news outlets. Third, given the absence of governor accounts from the network, central and regional governments may benefit from communicating their positions directly and, where possible, jointly, so that the public does not learn of intergovernmental disagreements only through third-party framing.

Data availability

The network data analysed in this study were collected from publicly available posts on X (formerly Twitter) using NodeXL Pro (version 1.0.1.553) with the query "Purbaya" AND "Gubernur" for 1–14 October 2025. The following materials will be deposited in Harvard Dataverse upon acceptance, and the DOI will be added at the proof stage: (i) the anonymised edge list and vertex list (1,373 accounts; 1,767 edges) with Post IDs, interaction type, cluster membership (G1–G14) and centrality metrics; (ii) the cleaned dataset used in the analysis; (iii) a data dictionary describing all variables and transformations; (iv) the codebook and the coded

dataset (Post IDs and assigned codes) for the qualitative content analysis; (v) the NodeXL data collection and analysis protocol; and (vi) the graph-metric outputs underlying Tables 1–4 and Figs. 3–11. The codebook and protocol are also provided as Supplementary Information 1 and 2. The full text of posts and identifying information on private users are not shared, because redistribution of X content is restricted by the X Developer Agreement and Policy and to protect the privacy of users who did not consent to research use; private accounts have therefore been pseudonymised, while accounts of public officials, government institutions and media organisations are retained. Files containing Post IDs are under restricted access and are available to editors and reviewers, and to other researchers for non-commercial research on reasonable request to the corresponding author. No questionnaire or survey was used in this study.

References

Al-Omoush KS, Garrido R, Cañero J (2023) The impact of government use of social media and social media contradictions on trust in government and citizens' attitudes in times of crisis. J Bus Res 159:113748. https://doi.org/10.1016/j.jbusres.2023.113748

Amores JJ, González-Baquero W, Oller-Alonso M (2025) Toxicity levels in Spanish political communication on Twitter/X: a comparative analysis of major political parties, 2015–2023. Front Political Sci 7:1–13. https://doi.org/10.3389/fpos.2025.1627474

Bastos MT, Raimundo RLG, Travitzki R (2013) Gatekeeping Twitter: message diffusion in political hashtags. Media Cult Soc 35(2):260–270. https://doi.org/10.1177/0163443712467594

Claeys A-S, Coombs WT (2019) Organizational crisis communication: suboptimal crisis response selection decisions and behavioral economics. Commun Theory. https://doi.org/10.1093/ct/qtz002

Coombs WT (2007) Protecting organization reputations during a crisis: the development and application of situational crisis communication theory. Corp Reput Rev 10(3):163–176. https://doi.org/10.1057/palgrave.crr.1550049

Coombs WT (2018) State of crisis communication: evidence and the bleeding edge. Institute for Public Relations

Coombs WT, Holladay SJ (1996) Communication and attributions in a crisis: an experimental study in crisis communication. J Public Relat Res 8(4):279–295. https://doi.org/10.1207/s1532754xjprr0804_04

Coombs WT, Holladay SJ (eds) (2022) The handbook of crisis communication, 2nd edn. Wiley-Blackwell. https://doi.org/10.1002/9781119678953

Coombs WT, Tachkova ER (2024) How emotions can enhance crisis communication: theorizing around moral outrage. J Public Relat Res 36(1):6–22. https://doi.org/10.1080/1062726X.2023.2244615

Durrheim K, Schuld M (2025) Polarization on social media: comparing the dynamics of interaction networks and language-based opinion distributions. Polit Psychol 46(6):1601–1617. https://doi.org/10.1111/pops.70000

Elgueta-Ruiz Á, Sadi G, Gonçalves G, Martínez-Ortiz J (2026) Meta-research on crisis communication: 24 years of research in Public Relations Review (2000–2023). Public Relat Rev 52(2):102685. https://doi.org/10.1016/j.pubrev.2026.102685

Ellis CH, Evans CEL, Moore JB (2024) Social network and sentiment analysis of the #Nutrition discourse on Twitter. Proceedings 91(1):301. https://doi.org/10.3390/proceedings2023091301

Faustyna F, Younus M (2026) The social network analysis (SNA) using NodeXL for sports tourism promotion: a case study of Aceh and North Sumatra. Humanit Soc Sci Commun 13:846. https://doi.org/10.1057/s41599-026-07160-9

Golan GJ, Himelboim I (2016) Can world system theory predict news flow on Twitter? The case of government-sponsored broadcasting. Inf Commun Soc 19(8):1150–1170. https://doi.org/10.1080/1369118X.2015.1106572

Habermas J (1991) The structural transformation of the public sphere: an inquiry into a category of bourgeois society (trans: Burger T). MIT Press, Cambridge, MA

Han X, Baird C (2024) Government crisis messaging on social media, citizen online engagement and compliance with policies. Public Manag Rev 26(3):613–634. https://doi.org/10.1080/14719037.2022.2103843

Hansen DL, Shneiderman B, Smith MA, Himelboim I (2019) Analyzing social media networks with NodeXL: insights from a connected world, 2nd edn. Morgan Kaufmann, Cambridge, MA

Himelboim I, Golan GJ, Moon BB, Suto RJ (2014) A social networks approach to public relations on Twitter: social mediators and mediated public relations. J Public Relat Res 26(4):359–379. https://doi.org/10.1080/1062726X.2014.908724

Jong W (2025) Beyond the snapshot: rethinking crisis communication theories in dynamic crisis situations. Public Relat Rev 51(3):102586. https://doi.org/10.1016/j.pubrev.2025.102586

Kemp S (2025) Digital 2025: Indonesia. DataReportal. https://datareportal.com/reports/digital-2025-indonesia. Accessed 25 October 2026

Li J, Cheng Y, Ahmad T (2026) Advancing theory in social media-mediated crisis communication research in China: a mixed-method review. Public Relat Rev 52(3):102710. https://doi.org/10.1016/j.pubrev.2026.102710

Logan-McFarlane A (2025) #KateGate: how the passionate energy of publics' social media posts affected the royal communications crisis. Public Relat Rev 51(3):102590. https://doi.org/10.1016/j.pubrev.2025.102590

Pond P, Lewis J (2019) Riots and Twitter: connective politics, social media and framing discourses in the digital public sphere. Inf Commun Soc 22(2):213–231. https://doi.org/10.1080/1369118X.2017.1366539

Recuero R, Zago G, Soares F (2019) Using social network analysis and social capital to identify user roles on polarized political conversations on Twitter. Soc Media Soc 5(2). https://doi.org/10.1177/2056305119848745

Reveilhac M, Trembovelskyi B (2025) Analyzing the share of media followers of government Twitter accounts across Western European countries. Eur J Commun 40(2):121–143. https://doi.org/10.1177/02673231251315911

Rustamaji HC, Kusuma WA, Nurdiati S, Batubara I (2024) Community detection with Greedy Modularity disassembly strategy. Sci Rep 14(1):1–17. https://doi.org/10.1038/s41598-024-55190-7

Schäfer MS (2016) Digital public sphere. In: Mazzoleni G (ed) The international encyclopedia of political communication. Wiley-Blackwell, pp 1–7. https://doi.org/10.1002/9781118541555.wbiepc087

Staab P, Thiel T (2022) Social media and the digital structural transformation of the public sphere. Theory Cult Soc 39(4):129–143. https://doi.org/10.1177/02632764221103527

Vo DT, Bui LQ, Nguyen LVT, Nguyen NP, Phung T, Dinh M (2026) Beyond fear: moral framing and storyteller in fostering trust, joy, and hope in climate-driven crisis communication within collectivist culture. Public Relat Rev 52(2):102686. https://doi.org/10.1016/j.pubrev.2026.102686

Wakita K, Tsurumi T (2007) Finding community structure in mega-scale social networks [extended abstract]. In: Proceedings of the 16th International World Wide Web Conference (WWW 2007). ACM, pp 1275–1276. https://doi.org/10.1145/1242572.1242805

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Author contributions

Faustyna: conceptualisation, data collection, network analysis, writing original draft. Puji Santoso: methodology, qualitative content analysis, writing review and editing. Muhammad Younus: theoretical framework, validation, writing review and editing. All authors read and approved the final manuscript.

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Ethical approval

This research analyzes publicly available posts on X and does not involve any interaction with or intervention upon human participants. All procedures were conducted in accordance with applicable guidelines and regulations.

Competing interests

The authors declare no competing interests.

Informed consent

This study did not involve direct human participants, interviews, surveys, or experimental procedures requiring informed consent. The research relied exclusively on publicly available data obtained from the social media platform X (formerly Twitter) through NodeXL Pro. All analyzed content consisted of publicly accessible posts and interactions that users voluntarily shared on the platform. No private accounts or restricted data were collected or analyzed, and in the shared dataset the handles of private individuals have been pseudonymised (see "Data availability"). Therefore, informed consent from individual users was not required in accordance with institutional research ethics guidelines and standard ethical practices for studies involving publicly available social media data.

Additional information

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