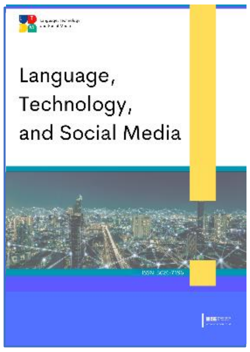

WISE Pendidikan Indonesia

LANGUAGE, TECHNOLOGY, AND SOCIAL MEDIA

ISSN: 3026-7196

Communicative Roles and Structural Fragmentation in LPDP Scholarship Discourse on Platform X

Fathiyyah Azizah*✉, Nadya Tristina✉, Elisabeth Satya Wacana Patricia S✉, Reni Nuraeni✉, and Ai Indah Cahyani✉

To cite this article. F. Azizah, N. Tristina, E. S. W. P. S, R. Nuraeni, and A. I. Cahyani, "Communicative Roles and Structural Fragmentation in LPDP Scholarship Discourse on Platform X," *Lang. Technol. Soc. Media*, vol. 4, no. 3, pp. 534–548, 2026.
DOI: https://doi.org/10.70211/ltsm.3026-7196.531

To link to this article:

Published online: 15 September 2026

Submit an article to this journal

View crossmark data

Watch the video on YouTube

OPEN ACCESS

Language, Technology, and Social Media Vol 4 No 3 (2026) https://doi.org/10.70211/ltsm.3026-7196.531

Check for updates

Research Article

Communicative Roles and Structural Fragmentation in LPDP Scholarship Discourse on Platform X

Fathiyyah Azizah*, Nadya Tristina, Elisabeth Satya Wacana Patricia S, Reni Nuraeni, and Ai Indah Cahyani

Received: 26 May 2026	Revised: 22 June 2026	Accepted: 13 September 2026	Online: 15 September 2026

Abstract

Public discussion of scholarship policy involves different communicative activities, including seeking information, sharing experience, and questioning institutional accountability. Understanding how these activities connect requires attention to both network structure and the roles of technologically mediated accounts. This study examines LPDP scholarship discourse on Platform X from 1 January to 31 March 2026 using quantitative social network analysis. A corpus of 823 interaction-bearing public posts generated a directed network of 489 accounts and 386 unique edges. Five communities were reported, with modularity Q = 0.642. Centrality measures differentiated interaction destinations from initiating accounts and potential brokers: @grok had the highest in-degree (19) and a reported betweenness score of 0.00, whereas @tanyakanrl had the highest out-degree (16) and betweenness score (36.00). Interpreted through communication affordances and human–machine communication, these patterns indicate that receiving attention and occupying connecting positions are distinct communicative roles. The findings support structural fragmentation within the observed network, while thematic labels remain descriptive and do not establish ideological agreement or an echo chamber. The study contributes a role-sensitive interpretation of digital public discourse that separates observable interaction from message meaning and communicative influence. For institutional communication, it identifies potential points for examining how explanations enter conversations organized around different information needs.

Keywords: Digital Public Discourse; Communication Affordances; Human–Machine Communication; Structural Fragmentation; Social Network Analysis.

INTRODUCTION

Public-policy discussion on social media is organized through acts of addressing, responding, citing, and recirculating messages. An account may be prominent because others direct questions toward it, because it initiates interactions, or because it lies on paths connecting other accounts. These positions have different implications for communication. A single ranking of influential users can obscure the difference between attracting attention and connecting conversations, especially when a public discussion includes human participants, automated submission accounts, and an addressable AI account.

Digital communication research therefore requires a distinction between the arrangement of interactions and the meanings that participants negotiate through them. Affordances describe possibilities for action arising in the relationship between users and technologies; they should not be equated with interface features or assumed outcomes [1]. In this study, mentions, replies, reposts, and quote posts provide observable traces of interaction. Their aggregation makes relationships measurable, but the resulting graph cannot by itself establish agreement, persuasion, or mutual understanding.

This problem is particularly relevant to research on echo chambers. A recent systematic review describes a research field connecting network structure with exposure, content, and persuasion [2]. Indonesian network and discourse studies have examined institutional accountability, public-health communication, digital activism, and policy controversy [3]–[13]. Together, these studies provide an important context for investigating digital publics. The analytical challenge is to explain what a detected group represents when people may interact around a common issue for different communicative purposes.

LPDP scholarship discourse provides a setting in which this distinction matters. Discussion of a publicly funded scholarship program can encompass practical requests for information, accounts of educational experience, criticism of public spending, and humorous reactions. These activities concern the same institution but need not involve the same audience, expectations of response, or standards of relevance. The study examines how the observed interactions are organized across these potentially different conversational orientations, without assuming that a community label identifies a shared ideology.

The presence of @grok and automated submission accounts also complicates the conventional identification of opinion leaders. Human–machine communication scholarship treats communicative technologies as potential participants in meaning-making, rather than only as channels between people [14]. An AI account may be addressed as a source of explanation, while an autobase may relay submissions through an account identity distinct from their human originators. Network position is useful for distinguishing these roles, although claims about how users experience them require evidence beyond centrality scores.

The study asks three questions: (1) How are LPDP-related interactions organized into structural communities on Platform X? (2) How do incoming ties, outgoing ties, and betweenness distinguish the communicative positions of human, AI, and automated submission accounts? (3) What does the relationship between these positions and the descriptive community labels permit researchers to conclude about fragmentation and an echo chamber?

The contribution is a communication-centered interpretation of a bounded network. The analysis connects account roles to the organization of public interaction while separating structural connectivity from semantic agreement. LPDP is the empirical case through which this distinction is examined; the broader question concerns how public conversations are mediated when receiving attention, initiating interaction, and occupying connecting positions are distributed across different kinds of accounts.

LITERATURE REVIEW

Echo Chambers and Structural Fragmentation

An echo chamber is more specific than a visibly clustered network. Research on misinformation and selective exposure links the concept to repeated contact with congruent information, limited encounters with counter-attitudinal views, and reinforcement within socially or ideologically similar groups [15]–[18]. Network typologies can identify patterns of concentration and separation [19], but polarization also depends on exposure, opinion change, homophily, and the quality of debate [20]–[26]. High modularity is therefore evidence of structural separation, not sufficient proof of ideological closure.

Network Structure and Account Function

The distinction between a network pattern and a communication mechanism guides the analytical framework. Topic-network classification describes how interaction is organized [19], whereas an echo-chamber interpretation requires evidence about the information and viewpoints circulating within that structure [15]–[18]. The present study therefore separates three questions: how accounts cluster, which accounts receive or initiate ties, and which accounts occupy bridging positions. These structural questions can be addressed through network analysis; claims about belief reinforcement require additional evidence.

Addressing and Affiliation in Digital Discourse

Network connections and discursive affiliation describe related but different aspects of social interaction. Zappavigna shows how evaluative language and hashtags can support affiliation around shared values, including among users who are not engaged in a direct conversational exchange [27]. This distinction matters for the present design: a graph based on explicit account-to-account interactions can miss shared orientations expressed without such ties. Conversely, the existence of a reply or mention does not reveal whether participants share an evaluation. The network is therefore a map of recorded relational activity, not a complete representation of the social meanings surrounding LPDP.

Addressing an account establishes a publicly recorded relation to that account, but it may serve several communicative purposes. A reference can request clarification, attribute information, contest a statement, or invite another participant into a discussion. These are possible interpretations rather than coded categories in the present dataset. Distinguishing them would require examination of message content and conversational sequence. The analytical value of in-degree is consequently precise but limited: it identifies accounts toward which recorded actions were directed.

AI Accounts and Mediated Human Participation

Two forms of technological involvement need to be distinguished. Human–machine communication concerns interactions in which a machine is encountered as a communicator [14]. AI-mediated communication, as defined by Hancock and colleagues, concerns an intelligent agent modifying, augmenting, or generating messages on behalf of a human communicator [28]. An autobase that republishes submissions should not automatically be classified as either a generative AI system or an autonomous speaker. For this case, the observable account function provides a basis for comparison while the authorship and processing of individual messages remain outside the network measures.

Sundar's framework further separates the effects of cues associated with AI from the effects of interacting with its capabilities [29]. Applied as a sensitizing perspective, this suggests that addressing @grok and accepting its output are different phenomena. Incoming ties may locate where an AI account enters public interaction; they do not reveal whether users trusted it, considered it authoritative, or changed their understanding. The present analysis investigates this structural entry point without treating psychological responses to AI as measured outcomes.

Prior Research and the Present Study

The Indonesian studies reviewed above demonstrate the use of network and discourse approaches across institutional controversies, activism, and public-policy communication [3]–[13]. Their varied issue settings provide context for investigating LPDP discourse, but they do not establish the meaning of the communities detected in this case. Community detection identifies groups from network connections, while thematic or actor labels require separate interpretation [30]–[32]. This study applies that distinction to scholarship discourse by interpreting network positions alongside account functions and treating community themes as descriptive labels.

METHODS

The study used quantitative social network analysis to examine publicly observable interaction around LPDP on Platform X from 1 January to 31 March 2026.

Research Participants and Units of Analysis

The units of analysis were public posts, account nodes, and directed interactions. The analyzed network comprised 489 account nodes and 386 unique directed edges constructed from 823 interaction-bearing posts. Nodes represented accounts rather than individually recruited research participants.

Data Collection Procedure

Collection queries included "LPDP," "LPDP scholarship," associated institutional identifiers, relevant hashtags, and issue-specific terms. The initial retrieval contained 18,420 posts. Screening removed 2,615 duplicate records, 1,840 spam or automated low-value posts, 3,910 irrelevant posts, and 475 inaccessible posts, leaving 9,580 relevant posts. The network edge list was then constructed from 823 posts that contained at least one analyzable reply, mention, repost, or quote relation. These posts generated 489 account nodes and 386 unique directed edges.

A post was retained when it addressed the LPDP scholarship debate, scholarship accountability, public funding, or the associated citizenship and return-of-service discussion. Routine announcements, unrelated scholarship information, private or inaccessible posts, and off-topic keyword matches were excluded. Two reviewers independently assessed a random subset of 1,842 retrieved posts using the same criteria. Cohen's kappa was 0.84; disagreements were resolved through discussion.

Preprocessing comprised deduplication, account-type classification, relevance screening, and reviewer reconciliation. Repetitive cross-account text, extreme posting velocity, coordinated hashtag flooding, and commercial promotion were used to identify low-value automated activity. Functional automated actors were retained when they formed part of the observed communication infrastructure. These included autobase accounts that publish anonymous human submissions and the platform AI account @grok, which users directly mentioned in information requests.

Nodes represented user accounts. A directed edge from account A to account B represented an observable action initiated by A toward B through a mention, reply, repost, or quote post. Repeated interactions between a pair were stored as edge weights. Self-loops and isolates were excluded before analysis. The direction records the initiating action toward the referenced account. For a repost, this convention is different from the direction in which the original message may circulate from B to A's audience. Figure 1 summarizes the analytical sequence and its interpretation boundary.

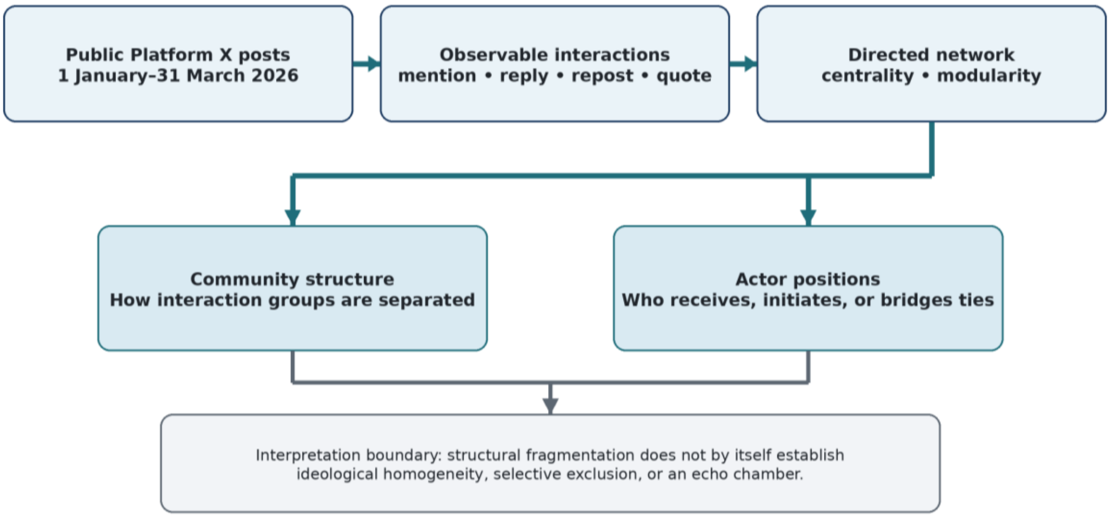

Figure 1. Analytical framework for constructing and interpreting the LPDP interaction network.

Data Analysis Procedure

Analysis was conducted in Gephi 0.10.1 on a directed, weighted graph. Raw degree counted all direct ties connected to an account; in-degree counted ties received; and out-degree counted ties initiated. Betweenness centrality was calculated with the Brandes shortest-path approach to identify accounts positioned between other nodes [33]. Because centrality values describe position rather than persuasion, prominence was interpreted according to each account's observable function.

Community detection examined whether interactions formed groups with comparatively denser internal than external connections. Prior research shows that diffusion topology can help distinguish information environments [34], while community detection requires attention to algorithmic assumptions, resolution limits, metadata, and alternative partitions [30]–[32], [35], [36]. The Louvain procedure was applied at resolution 1.0, producing five communities and modularity Q = 0.642. Descriptive community labels were assigned after inspection of associated accounts and posts; they were not generated by the modularity algorithm and were not treated as validated content categories.

Connecting Measures to Communicative Interpretation

The interpretation distinguishes three levels of evidence. Centrality and modularity summarize the observed topology. Account-function descriptions and community labels contextualize that topology. Claims about message meaning, stance, affiliation, or communicative influence would require content or reception evidence and are not treated as established findings. In-degree is interpreted as the receipt of recorded actions, out-degree as their initiation, and betweenness as a potential connecting position under the chosen path calculation.

Because the graph pools several interaction types, it does not preserve their distinct conversational meanings in the reported rankings. A reply and a repost can each create an edge while performing different communicative work. Similarly, repeated interactions stored as weights represent recorded frequency, not the intensity of agreement. The descriptive thematic labels in Table 3 contextualize the five communities; no formal stance, sentiment, speech-act, or linguistic affiliation coding is reported.

Ethical Considerations

Only publicly accessible posts and interaction metadata were analyzed. Ordinary users were not quoted in the article, and the results emphasize aggregate structures. Public or functional accounts were retained by handle when their network role was necessary to interpret the findings. The dataset did not include private messages or content from protected accounts.

RESULTS AND DISCUSSION

Results

Network overview

The final directed network contained 489 nodes and 386 unique edges. The small number of observed ties relative to the number of accounts indicates a sparse interaction structure, while modularity Q = 0.642 shows that the ties were organized into distinguishable communities. This combination supports structural fragmentation: many participants were connected through localized interaction patterns rather than through one integrated discussion. It does not, by itself, establish ideological polarization.

Figure 2 provides a schematic overview of the five community descriptions. It summarizes the reported account functions and thematic labels; the node arrangement and connecting lines are illustrative and should not be read as an exact export of the observed edge list. The community shares and anchor accounts are reported in Table 3.

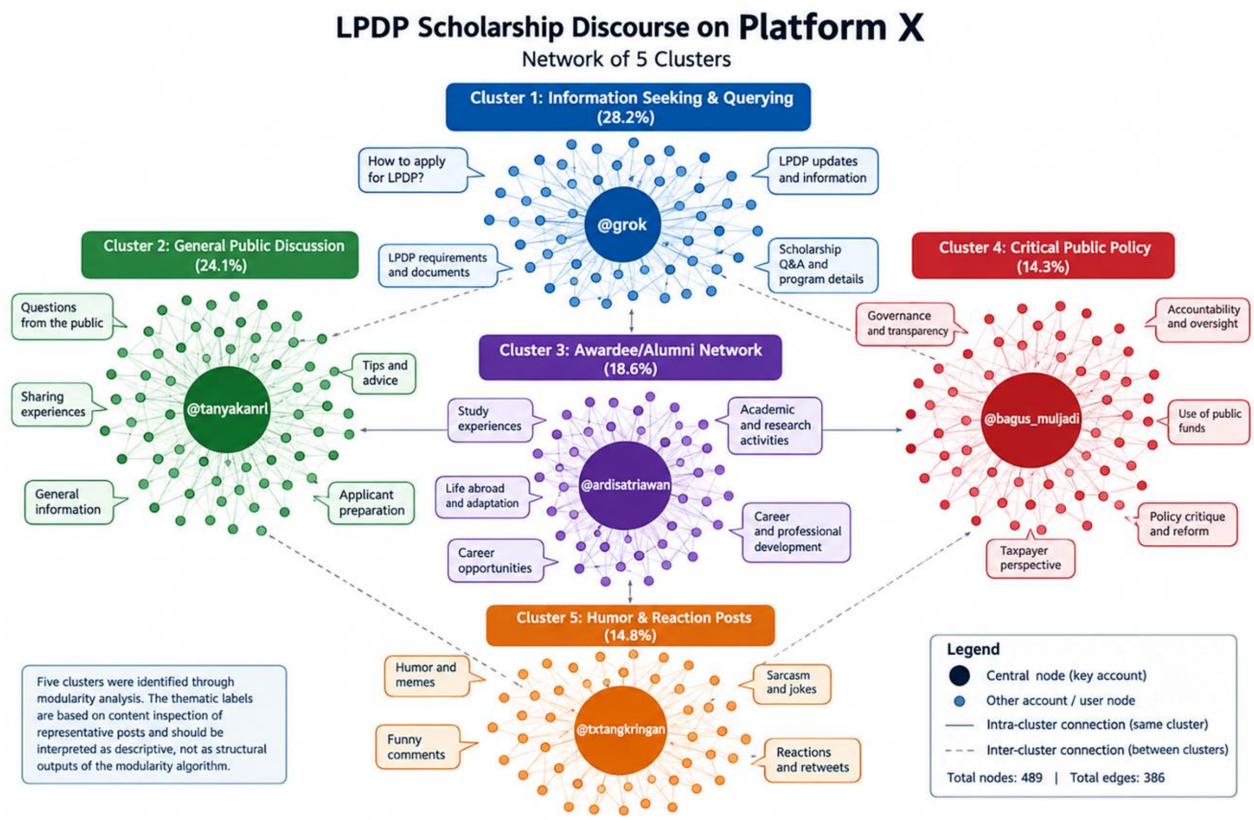

Figure 2. Schematic overview of the five community descriptions in LPDP discourse. Node placement and links are illustrative; reported community shares are summarized in Table 3.

Actor centrality and functional roles

Table 1 distinguishes incoming attention from initiating activity. @grok had the highest raw degree (20) and in-degree (19), identifying it principally as a destination for recorded actions. @tanyakanrl had the highest out-degree (16) and the second-highest raw degree (18), placing it more prominently on the initiating side of the aggregate interaction graph. Its known submission-relay function provides relevant context for that position. However, because the edge types are pooled, the out-degree value cannot establish how many ties represent original publication, responses, mentions, or recirculation.

Table 1. Top five accounts by raw degree, out-degree, and in-degree

Rank	Raw degree	Out-degree	In-degree
1	@grok (20)	@tanyakanrl (16)	@grok (19)
2	@tanyakanrl (18)	@tanyarlfes (10)	@joni_member (6)
3	@ardisatriawan (11)	@ardisatriawan (9)	@kolapakuin (4)
4	@tanyarlfes (10)	@dayatpiliang (8)	@ramazaynworld (4)
5	@dayatpiliang (10)	@bagus_muljadi (8)	@txtangkringan (3)

Source: processed research data, 2026.

Table 2 identifies a different dimension of prominence. @tanyakanrl had the highest reported betweenness score (36.00), followed by @ardisatriawan (18.50), @dayatpiliang (14.25), @bagus_muljadi (12.00), and @tanyarlfes (9.75). This ranking places @tanyakanrl on more of the shortest paths counted by the analysis than the other listed accounts. Its score suggests a potential brokerage position within the measured topology. Establishing brokerage specifically between the detected communities would additionally require an examination of cross-community paths and edges. The reported score for @grok was 0.00, distinguishing its incoming prominence from this form of structural brokerage.

Table 2. Top five accounts by betweenness centrality

Rank	Account	Betweenness	Interpretive boundary
1	@tanyakanrl	36.00	Potential brokerage; relay account
2	@ardisatriawan	18.50	Potential brokerage within the observed graph
3	@dayatpiliang	14.25	Potential brokerage within the observed graph
4	@bagus_muljadi	12.00	Potential brokerage; policy-discussion account
5	@tanyarlfes	9.75	Potential brokerage; relay account

Source: processed research data, 2026. Betweenness scores are reported as exported in the source analysis.

Figure 3 compares the reported centrality values across the leading accounts. The contrast between @grok and @tanyakanrl shows why receiving attention, initiating actions, and occupying shortest-path positions should be interpreted separately. The values describe the aggregated interaction topology; they do not trace the movement or reception of a particular message.

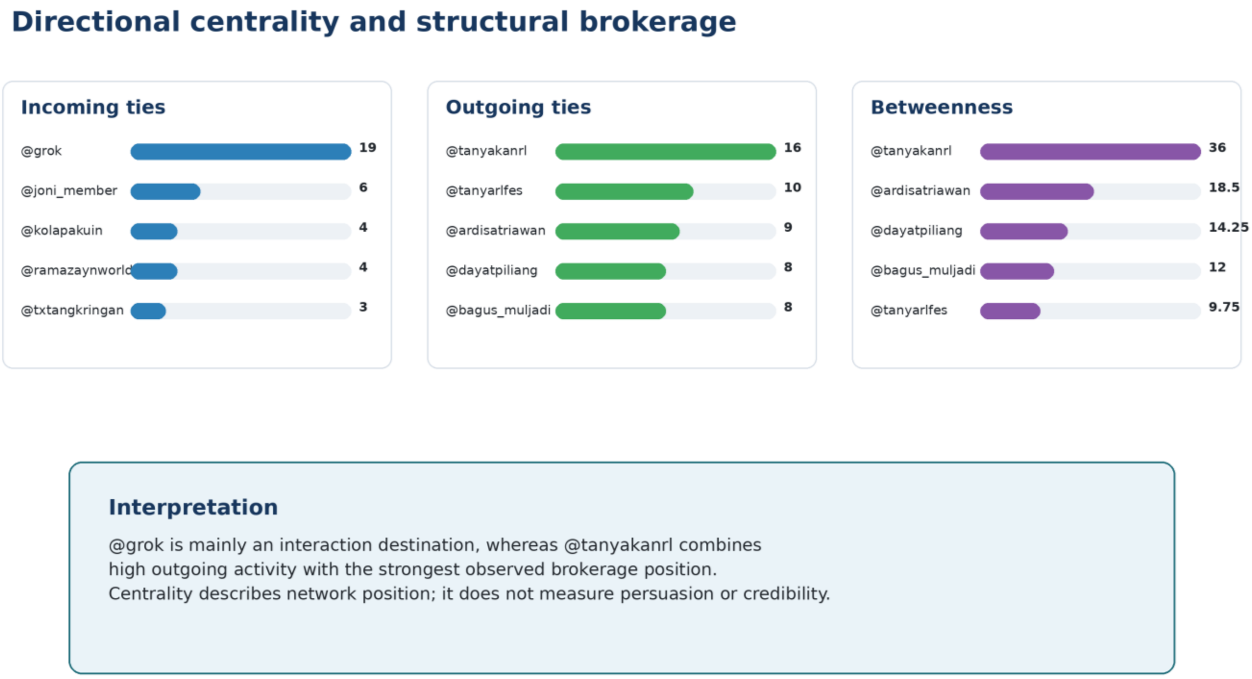

Figure 3. Incoming ties, outgoing ties, and betweenness among the leading accounts.

Community structure

The five communities together account for the detected modular structure. Table 3 lists their relative shares, anchor accounts, and descriptive focus. Community 1 was the largest (28.2%) and was associated with information seeking and AI-assisted queries. Community 2 (24.1%) centered on general questions and peer discussion through @tanyakanrl. Community 3 (18.6%) was associated with awardee and alumni experience, Community 4 (14.3%) with public-policy criticism, and Community 5 (14.8%) with humor and reaction posts.

Table 3. Detected communities and descriptive interpretation

Community	Share	Anchor	Descriptive focus
1	28.2%	@grok	Information seeking and AI-assisted queries
2	24.1%	@tanyakanrl	General public questions and peer discussion
3	18.6%	@ardisatriawan	Awardee and alumni experiences
4	14.3%	@bagus_muljadi	Public policy, transparency, and governance
5	14.8%	@txtangkringan	Humor, memes, and public reactions

Source: processed research data, 2026. Themes are descriptive labels based on inspection, not outputs of the modularity algorithm.

Discussion

Structural fragmentation rather than a confirmed echo chamber

The modular result is consistent with segmented interaction, but the evidence does not meet the stronger requirements of an echo-chamber claim. Experimental and observational studies show that exposure to opposing views can have contingent effects, while heterogeneous discussion networks may arise through accidental exposure, selective exposure, or platform-specific participation [37], [38]. Homophily can shape social ties [39], [40], and emotion or identity can affect diffusion [41], yet none of these mechanisms was measured here. The five LPDP communities may therefore reflect topic specialization and account function rather than ideological closure.

This interpretation also fits evidence that online information diets are more mixed than simple filter-bubble accounts imply. Large-scale studies find both selective exposure and meaningful cross-cutting contact [42], [43], and survey evidence suggests that echo-chamber effects may be overstated for people with diverse media use [44]. Cross-ideological interaction can occur even in polarized settings [45]. Conversely, hostile rumor sharing may be motivated by factors other than informational isolation [46], and politically selective exposure can occur without total exclusion of alternative news [47]. These findings support restraint: the present network identifies structural communities and differences in brokerage scores, without measuring shared beliefs or systematic rejection of opposing information.

Non-human actors and policy communication

The contrast between @grok and @tanyakanrl provides the central actor-level finding. The former combined high in-degree with no reported betweenness, while the latter combined high out-degree with the highest reported betweenness. The communicative interpretation concerns different positions within the interaction process: an account can attract requests or references without connecting shortest paths, and a submission-relay account can occupy a connecting position without being the original human author of the material associated with it.

For institutional communication, these patterns identify questions about where explanations are addressed and how they might enter different conversational settings. An institutional account could examine the questions directed toward AI accounts and the concerns relayed through submission accounts when preparing explanations. Any resulting intervention would need evaluation: the present data do not establish that a response would reach a particular audience, improve understanding, or change trust.

Fragmentation as Differentiated Communicative Activity

Read together, the community descriptions suggest an alternative to treating every modular partition as an ideological boundary. Practical information seeking, peer questions, accounts of scholarship experience, governance criticism, and humorous reactions may organize attention around different purposes. This is a plausible interpretation of the reported labels, not a finding that those purposes explain the network partition. Its value is to make the inference testable: a subsequent analysis could compare coded communicative functions within and across communities before deciding whether separation is mainly functional, topical, or ideological.

This perspective also changes the meaning of limited connectivity. Conversations may be weakly connected because participants seek different kinds of responses, because they interact at different times, or because the retrieval process captures only part of their activity. Ideological avoidance is one possible explanation among these alternatives. The network measures do not distinguish them. A communication-centered account therefore asks what forms of exchange link or separate participants, rather than assigning motives directly from the shape of the graph.

Attention and Brokerage as Distinct Communicative Positions

The @grok result illustrates that being addressed is analytically distinct from mediating connections. Its 19 incoming ties make it a prominent target within the measured network, but the score says little about the conversational quality of its responses. The pattern is compatible with an AI account becoming a publicly addressable resource; it does not demonstrate that the account supplied reliable explanations or displaced institutional expertise. Examining those possibilities would require the actual question–response sequences and evidence of how participants used the answers.

The @tanyakanrl result raises a complementary issue of attribution. An account-level graph represents the visible publishing or interacting identity. For a submission relay, that identity need not coincide with the human originator of each message. Consequently, attributing the account's structural position to the beliefs or persuasive capacity of a single actor would collapse distinct roles. The present findings support separating the origin of a contribution, its visible account identity, and the account's structural position when interpreting public interaction.

Implications for Explanation and Public Dialogue

The descriptive communities point to different potential demands on institutional explanation. Procedural questions call for accessible accounts of requirements and processes; accounts of experience may call for contextual clarification; governance criticism may call for reasons, evidence, and opportunities to question institutional decisions. These are implications inferred from the community descriptions, not evaluated communication strategies. Their common premise is that information availability and communicative adequacy are different: a statement may be publicly accessible while failing to address the question around which a conversation has formed.

The broader contribution is a disciplined connection between network analysis and the study of mediated public communication. The same policy topic can bring together different account types and conversational orientations without forming a single integrated public or a set of demonstrably closed echo chambers. The LPDP case shows how role-sensitive interpretation can extract communicative significance from topology while identifying the point at which discourse, sequence, or audience evidence becomes necessary. It offers an analytical distinction for comparative research rather than a general prediction about other platforms or policy debates.

CONCLUSION

LPDP-related interaction on Platform X formed a sparse directed network of 489 accounts and 386 unique edges derived from 823 interaction-bearing posts. Five communities were reported, with modularity Q = 0.642. The centrality results differentiated @grok as a prominent interaction destination from @tanyakanrl as an active initiator with the highest reported betweenness. These positions show that attention receipt and potential brokerage are distinct dimensions of mediated public communication. The network supports a finding of structural fragmentation, while the meanings of that fragmentation remain open to further investigation. The descriptive community labels suggest different conversational orientations, but neither ideological homogeneity nor an echo chamber was demonstrated. The study contributes by connecting structural measures to communicative roles and by making the boundary between interaction, interpretation, and influence explicit. Further research should link the archived interaction graph with message sequences, validated content coding, and audience evidence to examine how questions, explanations, criticism, and affiliative meanings move across these positions.

LIMITATIONS

The study is bounded by its January–March 2026 observation period and retrieval of public, accessible Platform X posts using specified search terms. Private, deleted, restricted, differently phrased, or unindexed content was unavailable. The 823 interaction-bearing posts represent a subset of the 9,580 screened relevant posts, so the network describes recorded relational activity rather than the entire issue public. Accounts and contributions without retained edges are not represented by the graph. Absence of a recorded tie cannot be interpreted as absence of exposure or participation. Several analytical limits affect the interpretation. Pooling mentions, replies, reposts, and quote posts obscures differences in communicative action and direction of message circulation. The reported betweenness values depend on the path calculation; normalization, treatment of edge weights as distances, and community-resolution sensitivity are not documented sufficiently to assess robustness. Community labels were not validated through a formal content-coding reliability test. The study did not measure stance, evaluation, affiliation, response quality, information accuracy, perceived AI agency, or changes in understanding and trust. Consequently, the evidence supports structural and role-based interpretation within this case, not causal or population-level claims. A stronger follow-up design would retain interaction types and timestamps, document the screening-to-network transition, and reproduce the metrics from the archived edge list and analysis settings. It could then compare community assignments with independently coded communicative functions and examine complete exchanges involving AI and submission accounts. This would allow direct tests of whether the observed partitions reflect different information needs, evaluative alignments, or persistent barriers to dialogue.

AUTHOR INFORMATION

Corresponding Authors

Fathiyyah Azizah– Communication Science, Universitas Ummi Bogor (Indonesia);
orcid.org/0009-0007-2866-0499
Email: fathiyyahazizah23@gmail.com

Authors

Fathiyyah Azizah– Communication Science, Universitas Ummi Bogor (Indonesia);
orcid.org/0009-0007-2866-0499
Nadya Tristina – Communication Science, Universitas Ummi Bogor (Indonesia);
orcid.org/0009-0005-5582-6998
Elisabeth Satya Wacana Patricia S – Communication Science, Universitas Ummi Bogor (Indonesia);
orcid.org/0009-0006-3992-3461
Reni Nuraeni – Digital Content Broadcasting, Telkom University Bandung (Indonesia);
orcid.org/0000-0003-1317-0503
Ai Indah Cahyani – Digital Content Broadcasting, Telkom University Bandung (Indonesia);
orcid.org/0009-0005-7733-7511

AUTHOR CONTRIBUTION

FA, NT, ES designed the research framework and formulated the research objectives. FA and NT conducted data collection and data scraping on platform X using Python. ES and RN performed Social Network Analysis (SNA) and interpreted the network visualization results using Gephi software. RN and AIC contributed to theoretical analysis, discussion development, and manuscript revision. FA coordinated the overall research process and finalized the manuscript for publication. All authors reviewed and approved the final version of the manuscript.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

DECLARATION OF USE OF AI IN SCIENTIFIC WRITING

The author(s) used ChatGPT by OpenAI during the preparation of this work to assist in language refinement, grammar correction, academic paraphrasing, manuscript structuring, and translation of several sections into academic English. After utilizing the tool/service, the author(s) thoroughly reviewed, revised, and edited the content as necessary and assumed full responsibility for the publication's content.

REFERENCES

[1] S. K. Evans, K. E. Pearce, J. Vitak, and J. W. Treem, "Explicating affordances: A conceptual framework for understanding affordances in communication research," *Journal of Computer-Mediated Communication*, vol. 22, no. 1, pp. 35–52, 2017. https://doi.org/10.1111/jcc4.12180

[2] J. J. P. Latupeirissa and N. M. W. Cistadewi, "A systematic review on social media echo chambers and political persuasion," *Jurnal Studi Komunikasi*, vol. 9, no. 2, pp. 562–576, 2025. https://doi.org/10.25139/jsk.v9i2.10041
[3] S. Sumartias, D. A. T. Pulubuhu, Sudarmono, A. N. Adi, and E. Ratnasari, "Democracy in the Indonesian digital public sphere: Social network analysis of Twitter users' responses to the issue of Nationalism Knowledge Test at the Corruption Eradication Commission (TWK-KPK)," *Jurnal Ilmu Sosial dan Ilmu Politik*, vol. 26, no. 3, pp. 240–257, 2023. https://doi.org/10.22146/jsp.70896
[4] P. N. Aisyah, G. N. Bakry, and N. A. Sjafirah, "Analisis jejaring sosial peran pers dalam penyebaran informasi terkait kebijakan PPKM," *Jurnal Komunikasi Global*, vol. 11, no. 1, pp. 43–65, 2022. https://doi.org/10.24815/jkg.v11i1.24555
[5] M. A. Akbar, M. A. B. Amril, R. Syahira, F. R. Latisha, and N. Jihan, "Analisis struktur jaringan komunikasi #SEAGAMES2022 di Twitter menggunakan pendekatan Social Network Analysis (SNA)," *Jurnal Studi Komunikasi dan Media*, vol. 26, no. 1, pp. 1–16, 2022. https://doi.org/10.17933/jskm.2022.4780
[6] A. S. B. Dahana, "Social Network Analysis percakapan pengguna X seputar isu pengungsi Rohingya di Indonesia," *Jurnal Pustaka Komunikasi*, vol. 8, no. 1, pp. 196–210, 2025. https://doi.org/10.32509/pustakom.v8i1.5000
[7] A. O. L. Hamanduna and P. Widjanarko, "Discourse network on the revision of Indonesian information and electronic transaction law," *Jurnal Studi Komunikasi*, vol. 7, no. 2, pp. 519–538, 2023. https://doi.org/10.25139/jsk.v7i2.5496
[8] M. I. Khatami, "Discourse network analysis (DNA): Aktivisme digital dalam perdebatan isu 'Presiden Tiga Periode' di Twitter," *Jurnal Audience*, vol. 5, no. 1, pp. 80–94, 2022. https://doi.org/10.33633/ja.v5i1.5484
[9] R. N. Priyansyah, R. R. Sulaiman, and F. R. Firdaus, "When the opposition dominates the conversation (Twitter network analysis about the controversial Indonesian Constitutional Court decision)," *Jurnal Komunikasi Indonesia*, vol. 13, no. 1, 2024. https://doi.org/10.7454/jkmi.v13i1.1221
[10] A. P. Bate and H. F. Amrullah, "Hashtag activism and football tragedy commemoration: Social network analysis in the #100harikanjuruhan hashtag on Twitter," *Jurnal Komunikasi Indonesia*, vol. 13, no. 1, 2024. https://doi.org/10.7454/jkmi.v13i1.1226
[11] E. Prihantoro and R. W. Ramadhani, "Social Network Analysis: #BlackLivesMatter distribution at actor level and system level," *Jurnal Komunikasi Ikatan Sarjana Komunikasi Indonesia*, vol. 6, no. 2, pp. 275–283, 2021. https://doi.org/10.25008/jkiski.v6i2.577
[12] L. Nurhajati, X. A. Wijayanto, L. R. Fitriyani, and D. Rachmawati, "Building democracy and freedom of expression by fighting the COVID-19 infodemic in the digital space among the younger generation in Indonesia," *Jurnal Komunikasi Ikatan Sarjana Komunikasi Indonesia*, vol. 8, no. 1, pp. 239–249, 2023. https://doi.org/10.25008/jkiski.v8i1.861
[13] C. N. Zempi and R. Rahayu, "Social media in the anticorruption movement: Social network analysis on the refusal of the 'Koruptor Boleh Nyaleg' decision on Twitter," *Jurnal Komunikasi Indonesia*, vol. 8, no. 2, 2019. https://doi.org/10.7454/jki.v8i2.11195
[14] A. L. Guzman and S. C. Lewis, "Artificial intelligence and communication: A Human–Machine Communication research agenda," *New Media & Society*, vol. 22, no. 1, pp. 70–86, 2020. https://doi.org/10.1177/1461444819858691
[15] M. Cinelli, G. De Francisci Morales, A. Galeazzi, W. Quattrociocchi, and M. Starnini, "The echo chamber effect on social media," *Proceedings of the National Academy of Sciences*, vol. 118, no. 9, Art. no. e2023301118, 2021. https://doi.org/10.1073/pnas.2023301118
[16] M. Del Vicario, A. Bessi, F. Zollo, F. Petroni, A. Scala, G. Caldarelli, H. E. Stanley, and W. Quattrociocchi, "The spreading of misinformation online," *Proceedings of the National Academy of Sciences*, vol. 113, no. 3, pp. 554–559, 2016. https://doi.org/10.1073/pnas.1517441113

[17] I. Himelboim, S. McCreery, and M. Smith, "Birds of a feather tweet together: Integrating network and content analyses to examine cross-ideology exposure on Twitter," *Journal of Computer-Mediated Communication*, vol. 18, no. 2, pp. 40–60, 2013. https://doi.org/10.1111/jcc4.12001

[18] I. Himelboim, K. D. Sweetser, S. F. Tinkham, K. Cameron, M. Danelo, and K. West, "Valence-based homophily on Twitter: Network analysis of emotions and political talk in the 2012 presidential election," *New Media & Society*, vol. 18, no. 7, pp. 1382–1400, 2016. https://doi.org/10.1177/1461444814555096

[19] I. Himelboim, M. A. Smith, L. Rainie, B. Shneiderman, and C. Espina, "Classifying Twitter topic-networks using social network analysis," *Social Media + Society*, vol. 3, no. 1, 2017. https://doi.org/10.1177/2056305117691545

[20] J. K. Lee, J. Choi, C. Kim, and Y. Kim, "Social media, network heterogeneity, and opinion polarization," *Journal of Communication*, vol. 64, no. 4, pp. 702–722, 2014. https://doi.org/10.1111/jcom.12077

[21] S. Messing and S. J. Westwood, "Selective exposure in the age of social media: Endorsements trump partisan source affiliation when selecting news online," *Communication Research*, vol. 41, no. 8, pp. 1042–1063, 2014. https://doi.org/10.1177/0093650212466406

[22] R. K. Garrett and N. J. Stroud, "Partisan paths to exposure diversity: Differences in pro- and counterattitudinal news consumption," *Journal of Communication*, vol. 64, no. 4, pp. 680–701, 2014. https://doi.org/10.1111/jcom.12105

[23] B. Enjolras and A. Salway, "Homophily and polarization on political Twitter during the 2017 Norwegian election," *Social Network Analysis and Mining*, vol. 13, Art. no. 10, 2023. https://doi.org/10.1007/s13278-022-01018-z

[24] P. Darius, "Who polarizes Twitter? Ideological polarization, partisan groups and strategic networked campaigning on Twitter during the 2017 and 2021 German Federal elections 'Bundestagswahlen'," *Social Network Analysis and Mining*, vol. 12, Art. no. 151, 2022. https://doi.org/10.1007/s13278-022-00958-w

[25] M. Osterbur and C. Kiel, "Tweeting in echo chambers? Analyzing Twitter discourse between American Jewish interest groups," *Journal of Information Technology & Politics*, vol. 18, no. 2, pp. 194–213, 2021. https://doi.org/10.1080/19331681.2020.1838396

[26] L. Iandoli, S. Primario, and G. Zollo, "The impact of group polarization on the quality of online debate in social media: A systematic literature review," *Technological Forecasting and Social Change*, vol. 170, Art. no. 120924, 2021. https://doi.org/10.1016/j.techfore.2021.120924

[27] M. Zappavigna, "Ambient affiliation: A linguistic perspective on Twitter," *New Media & Society*, vol. 13, no. 5, pp. 788–806, 2011. https://doi.org/10.1177/1461444810385097

[28] J. T. Hancock, M. Naaman, and K. Levy, "AI-mediated communication: Definition, research agenda, and ethical considerations," *Journal of Computer-Mediated Communication*, vol. 25, no. 1, pp. 89–100, 2020. https://doi.org/10.1093/jcmc/zmz022

[29] S. S. Sundar, "Rise of machine agency: A framework for studying the psychology of Human–AI Interaction (HAII)," *Journal of Computer-Mediated Communication*, vol. 25, no. 1, pp. 74–88, 2020. https://doi.org/10.1093/jcmc/zmz026

[30] M. Girvan and M. E. J. Newman, "Community structure in social and biological networks," *Proceedings of the National Academy of Sciences*, vol. 99, no. 12, pp. 7821–7826, 2002. https://doi.org/10.1073/pnas.122653799

[31] L. Peel, D. B. Larremore, and A. Clauset, "The ground truth about metadata and community detection in networks," *Science Advances*, vol. 3, no. 5, Art. no. e1602548, 2017. https://doi.org/10.1126/sciadv.1602548

[32] M. T. Schaub, J.-C. Delvenne, M. Rosvall, and R. Lambiotte, “The many facets of community detection in complex networks,” *Applied Network Science*, vol. 2, Art. no. 4, 2017. https://doi.org/10.1007/s41109-017-0023-6
[33] U. Brandes, “A faster algorithm for betweenness centrality,” *Journal of Mathematical Sociology*, vol. 25, no. 2, pp. 163–177, 2001. https://doi.org/10.1080/0022250X.2001.9990249
[34] F. Pierri, C. Piccardi, and S. Ceri, “Topology comparison of Twitter diffusion networks effectively reveals misleading information,” *Scientific Reports*, vol. 10, Art. no. 1372, 2020. https://doi.org/10.1038/s41598-020-58166-5
[35] V. A. Traag, L. Waltman, and N. J. van Eck, “From Louvain to Leiden: Guaranteeing well-connected communities,” *Scientific Reports*, vol. 9, Art. no. 5233, 2019. https://doi.org/10.1038/s41598-019-41695-z
[36] S. Fortunato and M. Barthélemy, “Resolution limit in community detection,” *Proceedings of the National Academy of Sciences*, vol. 104, no. 1, pp. 36–41, 2007. https://doi.org/10.1073/pnas.0605965104
[37] C. A. Bail, L. P. Argyle, T. W. Brown, J. P. Bumpus, H. Chen, M. B. F. Hunzaker, J. Lee, M. Mann, F. Merhout, and A. Volfovsky, “Exposure to opposing views on social media can increase political polarization,” *Proceedings of the National Academy of Sciences*, vol. 115, no. 37, pp. 9216–9221, 2018. https://doi.org/10.1073/pnas.1804840115
[38] J. Brundidge, “Encountering ‘difference’ in the contemporary public sphere: The contribution of the Internet to the heterogeneity of political discussion networks,” *Journal of Communication*, vol. 60, no. 4, pp. 680–700, 2010. https://doi.org/10.1111/j.1460-2466.2010.01509.x
[39] G. A. Huber and N. Malhotra, “Political homophily in social relationships: Evidence from online dating behavior,” *Journal of Politics*, vol. 79, no. 1, pp. 269–283, 2017. https://doi.org/10.1086/687533
[40] L. M. Aiello, A. Barrat, R. Schifanella, C. Cattuto, B. Markines, and F. Menczer, “Friendship prediction and homophily in social media,” *ACM Transactions on the Web*, vol. 6, no. 2, Art. no. 9, 2012. https://doi.org/10.1145/2180861.2180866
[41] F. Zollo, P. K. Novak, M. Del Vicario, A. Bessi, I. Mozetič, A. Scala, G. Caldarelli, and W. Quattrociocchi, “Emotional dynamics in the age of misinformation,” *PLoS ONE*, vol. 10, no. 9, Art. no. e0138740, 2015. https://doi.org/10.1371/journal.pone.0138740
[42] E. Bakshy, S. Messing, and L. A. Adamic, “Exposure to ideologically diverse news and opinion on Facebook,” *Science*, vol. 348, no. 6239, pp. 1130–1132, 2015. https://doi.org/10.1126/science.aaa1160
[43] S. Flaxman, S. Goel, and J. M. Rao, “Filter bubbles, echo chambers, and online news consumption,” *Public Opinion Quarterly*, vol. 80, no. S1, pp. 298–320, 2016. https://doi.org/10.1093/poq/nfw006
[44] E. Dubois and G. Blank, “The echo chamber is overstated: The moderating effect of political interest and diverse media,” *Information, Communication & Society*, vol. 21, no. 5, pp. 729–745, 2018. https://doi.org/10.1080/1369118X.2018.1428656
[45] P. Barberá, J. T. Jost, J. Nagler, J. A. Tucker, and R. Bonneau, “Tweeting from left to right: Is online political communication more than an echo chamber?” *Psychological Science*, vol. 26, no. 10, pp. 1531–1542, 2015. https://doi.org/10.1177/0956797615594620
[46] M. B. Petersen, A. Osmundsen, and K. Arceneaux, “The ‘need for chaos’ and motivations to share hostile political rumors,” *American Political Science Review*, vol. 117, no. 4, pp. 1486–1505, 2023. https://doi.org/10.1017/S0003055422001447
[47] R. K. Garrett, “Echo chambers online? Politically motivated selective exposure among Internet news users,” *Journal of Computer-Mediated Communication*, vol. 14, no. 2, pp. 265–285, 2009. https://doi.org/10.1111/j.1083-6101.2009.01440.x