Open Access Indonesia Journal of Social Sciences

Vol. 9 · No. 6 · 2026 · pp. 359–378 · Article ID 341

e-ISSN 2722-4252 · *Journal homepage: journalsocialsciences.com/index.php/oaijss*

ORIGINAL ARTICLE

Connective–Disconnective Youth Activism, Algorithmic Visibility Tactics, and Affective Polarization in Hybrid Media Ecosystems: Cross-Platform Network Analysis and Digital Ethnographic Inquiry

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ARTICLE INFORMATION

Received: October 1, 2026
Revised: October 15, 2026
Accepted: November 15, 2026
Available Online: December 22, 2026
Published: December 30, 2026

Keywords: Affective polarization; Algospeak; Connective and disconnective action; Digital ethnography; fsQCA; Network analysis; OONI; Youth activism

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DOI: https://doi.org/10.37275/oaijss.v9i6.341

ABSTRACT

Background: Connective action theory assumes neutral digital channels and spontaneous cross-cutting diffusion. Global South youth movements face network throttling, opaque recommender feeds, cyber-troop counter-operations, and material precarity, and they move between protest, coded 'algospeak', and disconnective exit.

Objective: To examine how Indonesian youth contention moves along this connective–disconnective continuum across infrastructure, network, platform, and discourse layers.

Methods: We analyzed 190,646 public records in four tiers. Tier 1 used OONI telemetry from Indonesia and six comparison countries (10,068,658 web probes over 1,002 days). Tier 2 modeled X protest networks (29,289 tweets, 11,426 actors) with Louvain communities, AIPW, and RIF quantile regressions, and Tier 3 added 4,768 #KaburAjaDulu posts, 57,362 nested TikTok comments, 9,882 human-coded comments, and digital ethnography. Tier 4 was a four-value fsQCA of 24 mobilization regimes.

Results: Probe volume was higher in protest windows (+0.268 log, p = 0.0317). The rise came from Wave 3 (August–September 2025; 35,701.8 probes/day), while February 2025 fell below baseline. Grassroots accounts were 99.21% of 1,010 Diffusion Drivers, who had 1.032 higher log views (z = 13.86), and porosity was higher after the late-August 2025 shock (0.0516 to 0.0956, p = 0.0029). On TikTok, nested replies were 3.53 percentage points more often classifier-negative ($p = 1.57 \times 10^{-11}$). Broad reach (consistency 0.8277) combined algorithmic tactics, bridging, moral grievance, connective voice, and porous deliberation.

Conclusion: The findings fit a connective–disconnective continuum. They point to anti-throttling transparency, visibility audits, bridge-rewarding feed design, and youth inclusion as measures to test.

All authors approved the final version of the manuscript.

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1. Introduction

1.1. From connective optimism to a connective–disconnective continuum in youth contention

For over a decade, scholarship on digital social movements has rested on the paradigm of 'connective action'.[1] The idea was simple. Personalized content sharing across social media networks lets young citizens coordinate large-scale contention without the bureaucratic brokerage of traditional civic organizations, and no formal leadership is needed. Hybrid media ecosystems complicate this picture. Pure connective voice now collides with platform commercialization, state surveillance, and civic fatigue. Recent work in New Media & Society describes digital contention that goes beyond amplifying voice and also includes 'disconnective action': deliberate, loosely coordinated practices of boycotting, unfollowing, opting out, and severing communicative or economic ties with unresponsive institutions.[2] Safety considerations matter. When people feel unsafe, they can reshape participation repertoires by curating their messaging groups through disconnection, and some young activists in high-risk and surveilled environments retreat from exposed public timelines into encrypted instant-messaging groups and tactical silence.[3,4] In polarized Twitterspheres, disconnective unfollowing and blocking are linked to a more fragmented partisan public sphere.[5]

We use 'connective–disconnective continuum' as our own descriptive term for the range of repertoires between public collective voice and withdrawal. To understand how contemporary youth move along it, three things need attention: spatial scale shifts, temporal protest rhythms, and Global South socio-economic realities. Hybrid mobilizations depend on dynamic scale shifts that carry localized grievances across places, issues, and borders.[6] Platformized spectacle, meanwhile, can foster outsourced and depoliticized forms of activism.[7,8] A temporal analysis of one sustained protest episode on X (formerly Twitter) shows mobilization and coordination messaging shifting over the episode.[9] Comparative frameworks now allow systematic comparison of how political actors use calls to action across platforms.[10] In several Global South settings, social media, including Twitter/X, have served as an agonistic counter-public for youth activism and for elite accountability 'dragging.' Examples include #EndSARS in Nigeria,[11] connective resistance against military rule during Myanmar's Spring Revolution,[12] and pan-Asian youth solidarity and politicized consumer boycotts across the Milk Tea Alliance.[13,14] Social-movement scholars also stress three pressures on youth movements. One is participant attrition and cohort turnover, which require continuous informal

knowledge transmission.[15] Another is the alignment of spatial-digital affordances between street protest sites and online feeds.[16] The third is cross-territorial grievance spillover.[17] In megacities such as Jakarta, Indonesia, urban youth hold moderate internet skills on average. Structural socio-economic inequalities also stratify who gains tangible outcomes from digital engagement.[18]

1.2. Algorithmic visibility tactics, algospeak, and TikTok's social interest clusters

Algorithms have transformed platform architectures themselves. That complicates youth contention further. Contemporary recommender systems are far from neutral town squares. They curate visibility through opaque engagement weighting and automated moderation classifiers, and marginalized and activist users respond with sustained 'algorithmic training' labor to combat shadowbanning and algorithmic injustice.[19–21] Gerbaudo shows what the rise of TikTok has done. Follower-graph 'social networks' are giving way to algorithmically assembled 'social interest clusters,' governed by behavioral similarity signals on the For-You Page (FYP).[22] Within these uneven topologies of online visibility,[23] content creators and grassroots organizers in precarious political contexts must practice 'strategic visibility.' They calibrate when to court viral reach and when to camouflage dissent.[24–26] They also face ephemeral visibility cycles that, as among fan communities, accelerate collective data work.[27] And they resist algorithmic suppression by automated platform governance.[20,21,28]

Young digital natives need to get around automated keyword demotion and state cyber-patrols. They must do so without sacrificing viral discoverability. Their answer is 'algospeak.' It covers creative orthographic respellings, phonetic abbreviations, numeric ciphers, and ironic multimodal metaphors, all designed to evade moderation filters while staying instantly legible to in-group peers.[29] Semiotic analyses indicate that algospeak is more than defensive censorship evasion. It is also playful algorithmic negotiation and subcultural boundary-making.[30] Platform affordances differ. Cross-platform studies show that platform affordances create divergent discursive opportunities for movement framing, which suggests that X's quote-tweet cascade graph and short-video nested comment trees may differ in what they afford.[31] On TikTok, memetic audio-visual templates and ironic satire empower youth anti-racist and civic mobilization.[32,33] Far-right actors, however, frequently dominate polarized TikTok debates on protest, and hostile engagement can amplify antagonism.[34] TikTok users, meanwhile, repurpose platform visibility for algorithmic mutual aid.[35]

1.3. Affective polarization, cyber-troop counter-framing, and network interference in Indonesia

One question remains central and unresolved in political communication. Do these algorithmic visibility tactics empower cross-cutting democratic solidarity, or do they accelerate affective polarization? Agent-based and empirical network models suggest that digital media may intensify affective polarization, and that the mechanism is not simply isolation inside closed filter bubbles. Exposure to decontextualized out-group conflict can drive partisan identity sorting.[36] Longitudinal and experimental evidence on social media use and later polarization is mixed.[37,38] Comparative cross-national evidence indicates that systemic affective polarization moderates the relationship between social media engagement and political participation,[39] and empirical conclusions depend on how partisan slant and affective polarization are measured.[40,41] Audience responses to emotional cues differ between platforms.[42] Incivility is frequent in online comment sections, although cross-cutting expression can also coincide with reasoned argument.[43] Network-activated frames, in turn, can amplify perceived polarization when partisans share more than nonpartisans.[44]

Indonesia is the flagship electoral democracy of Southeast Asia. There, these socio-technical dynamics meet organized domestic influence operations and episodic network friction. Extensive ethnographic and network investigations in The International Journal of Press/Politics and Indonesia document how paid and state-aligned cyber troops ('buzzers') run coordinated influence operations on social media,[45] including efforts to weaken anti-corruption institutions[46] and to intimidate journalists.[47] A human–computer interaction study of Iran's 2019 shutdown adds a warning. During street protests, states can pair discursive influence operations with infrastructure-level internet shutdowns, and citizens may answer by counter-appropriating the network.[48]

Between August 2024 and September 2025, Indonesia experienced a sequence of hybrid youth contention. That sequence illustrates all three theoretical puzzles. It had four parts. (a) The August 2024 #PeringatanDarurat ('Emergency Warning' Blue Garuda) and #KawalPutusanMK mobilization defended Constitutional Court electoral thresholds. (b) In January–February 2025, #IndonesiaGelap ('Dark Indonesia' student austerity/governance protests) erupted alongside #KaburAjaDulu ('Just Escape First'), a large youth wave that shared overseas visa, scholarship, and migration exit blueprints. (c) The August–September 2025 parliamentary and police-accountability unrest was galvanized by the fatal striking of gig-economy motorcycle-taxi driver Affan Kurniawan. (d) Heated TikTok comment contention arose over flagship state populist programs such as *Makan Bergizi Gratis* (MBG, Free Nutritious Meals). This study integrates four SHA-256-verified empirical tiers across 190,646 public records. The study answers three research questions. (RQ1) How do state/ISP network anomalies and citizen censorship-monitoring probes behave during major Indonesian youth protest waves, compared with regional hybrid protest polities? (RQ2) How do grassroots bridge brokers, quote-framing tactics, and moral shocks reshape cross-community visibility and Louvain porosity on X, versus nested reply-tree affective polarization on TikTok and disconnective exit in #KaburAjaDulu? (RQ3) Which set-theoretic configurations of algorithmic tactics, bridge brokerage, moral grievances, connective voice, and porous deliberation generate sustained cross-cutting civic reach, and which generate affective echo-chamber encapsulation?

2. Methods

2.1. Data sources, OONI telemetry, and research ethics

Systematic methodological critiques have urged digital-activism scholars to move beyond single-platform convenience snapshots[49,50] and segmented network silos.[51] Our response is a four-tier empirical architecture. It rests on 190,646 public records (51.01 MB across 9 archives) whose file integrity was checked with SHA-256 checksums; the authors generated no synthetic or simulated data. Tier 1 captures infrastructure-layer censorship and network-interference telemetry. Data come directly from the official Open Observatory of Network Interference (OONI REST API

v1).[52] For Indonesia we retrieve 5,010 daily-test aggregation records. They span 1,002 consecutive days (January 1, 2023 – October 1, 2025) and cover web_connectivity (10,068,658 individual probe measurements, 542,119 confirmed blocks, and 448,364 anomalies), encrypted instant messengers (Telegram, WhatsApp, Signal), and Psiphon circumvention. Alongside these sit 14,428 comparative daily-test records (May 2024 – October 2025) from seven Asian and Global South youth-protest polities: Indonesia, Thailand, Myanmar, Bangladesh, Kenya, the Philippines, and Malaysia (note that the Philippines' 99.96% Psiphon flag reflects carrier-specific mobile TLS middlebox handshake timeouts rather than nationwide statutory banning).

Tier 2 assembles three sequential waves of Indonesian X (Twitter) connective protest data. The first is the complete CC-BY-4.0 August–September 2025 Indonesian Digital Protest Network repository, curated by Rahmandika, Ramadhani, and Alamsyah. It comprises 29,289 irreversibly one-way SHA-hashed protest tweets (Book62-hashed.csv), 13,994 directed interaction edges, and 11,426 structural actor profiles across 1,667 Louvain communities, plus 3,966 multi-hop cascade records, pre/post-shift Louvain community porosity matrices (N = 194 community-phase observations), and seven narrative Cognitive Fusion and Excitation tables. The second is the February 18–27, 2025 #IndonesiaGelap social-network archive (3,054 tweets, 2,364 nodes, 2,998 edges). The third holds 1,567 tweets from the July–August 2024 #KawalPutusanMK constitutional protest wave. Tier 3 pairs 4,768 unique X posts from the 2025 #KaburAjaDulu disconnective youth exit wave (4,597 sentiment-labeled utterances plus viral benchmark threads) with 57,362 nested TikTok comment-tree records. These debate Indonesia's *Makan Bergizi Gratis* (MBG) policy.[53] Each preserves the exact parent–child reply hierarchy (level 0 top-level comments vs. level >= 1 nested replies). Independent predictions come from four Indonesian transformer sentiment models (taufiqdp, agufsamudra, mdhugol, and aardiiiiy). An independent benchmark of 9,882 human-linguist annotated Indonesian TikTok comments serves for validation. Ethical handling follows the Association of Internet Researchers (AoIR 3.0) standards for contentious digital environments.[54] All personal handles are irreversibly hashed or stripped prior to analysis and ethnographic reporting.

2.2. Data-linkage forensics, Louvain porosity, and cascade metrics

A bug surfaced. During data-integrity verification of the upstream August–September 2025 Indonesian Protest Network archive, our diagnostic audit uncovered a subtle string-normalization bug in the merged actor table (actor_engagement_structural_merged_hashed.csv). Raw tweets in Book62-hashed.csv prepend an '@' symbol to hashed handles (e.g., '@22ee35f7d5'). Network node tables omit it ('22ee35f7d5'). The upstream join therefore recorded zero views and missing tweet counts across all 11,426 nodes. Stripping leading '@' characters and re-aggregating exact tweet-level metrics recovers 7,583 active posting network actors, who together account for 31,130,601 cumulative tweet views. The remaining 3,843 nodes are pure passive targets, mentioned or replied to without authoring in-corpus protest posts.

Take the directed interaction graph G = (V, E), with 11,426 vertices and 13,994 weighted edges partitioned into 1,667 Louvain modularity communities.[55] Actors fall into three roles. (1) Diffusion Drivers (n = 1,010) are active outward bridge brokers with cross_comm_out >= 1. (2) Local Amplifiers (n = 6,163) are active senders whose ties remain 100% inside their own Louvain community. (3) Attention Sinks (n = 4,253) have zero outward protest ties. They absorb incoming mentions and replies. Community porosity $P_c = E_{c,ext} / E_{c,tot}$ is the share of cross-community edges. We evaluate it before (n = 113 active communities) and after (n = 81 active communities) the late-August 2025 moral shock of Affan Kurniawan's death, using both Welch's t-test and nonparametric Mann–Whitney U tests. Within the seven BERTopic narrative streams, the Cognitive Fusion Index (CFI) standardizes and averages z-scores of four measures: maximum cascade hop depth, mean hop depth, community porosity, and unique inter-community pairs.

2.3. Doubly robust AIPW, RIF quantile regressions, and classifier divergence

Social-media impressions and comment hostility are heavily skewed. Viral attention piles up in the upper tail. Mean OLS regressions alone therefore miss sharp distributional shifts between grassroots participants and mega-hubs. We estimate Firpo–Fortin–Lemieux Recentered Influence Function (RIF) unconditional quantile regressions,[56] a method related to the quantile regression framework of Rios-Avila and Maroto,[56,57] at τ in (0.10, 0.25, 0.50, 0.75, 0.90). Each model uses Gaussian Silverman kernel density bandwidths and MacKinnon–White HC3 robust standard errors.[58] Two domains are covered. In (a), the outcome is log cumulative actor views across all N = 7,583 active posting X protest nodes, and we test how Diffusion Driver bridge brokerage and log in-degree hub centrality operate from Q10 to Q90. In (b), the outcome is the classifier-negative comment share (%), which we use as an operational measure of negative sentiment and not as a direct measure of out-group hostility, across active TikTok Video × Hour contention windows (>= 25 comments/hour, derived from the 57,362 MBG comments). Here we test how nested reply-tree share (level >= 1) and typographic/algospeak visibility-tactic share shape thread hostility across Q10–Q90.

To estimate differences net of observable confounding, we use Doubly Robust Augmented Inverse-Probability Weighting (AIPW) models.[59] Propensity scores come from IRLS logistic models, clipped to (0.05, 0.95). Standard errors rest on a 120-draw nonparametric bootstrap. Each model comes with standardized mean difference (SMD) covariate-balance checks, VanderWeele E-values,[60] and Cinelli–Hazlett robustness values (RV_q).[61] Three contrasts follow. (1) Grassroots Bridge Brokerage (Diffusion Driver vs. Local Amplifier) among N = 7,170 active X protest initiators, controlling for grassroots status, log followers, and log in-degree. (2) Quote-Framing Visibility Tactics on X (is_quote = 1 vs. 0), across N = 29,289 tweets, with controls for log followers, account verification, and coded algospeak markers. (3) Nested Reply-Tree Threading (level >= 1 vs. top-level 0) together with Typographic/Coded Visibility Tactics on TikTok, covering N = 57,362 comments with controls for log character length and parent-video log comment volume. Each contrast predicts two outcomes. One is 4-classifier consensus negative affect. The other is 4-classifier disagreement (a 'pragmatic split'), which is coded 1 when the four independent NLP models split 1–3, 2–2, or 3–1 between negative and neutral/positive. Posting volume (tweets per actor) is not among the covariates of the first contrast; because Diffusion Drivers post more than Local Amplifiers (4.72 versus 1.38 tweets on average, Table 2), that estimate is an adjusted association. The visibility-tactic

code includes ALL-CAPS and punctuation, which also signal emphasis or anger, so its association with negative sentiment is partly built into the code.

2.4. Digital ethnography, four-value fsQCA, and joint-display integration

Recent work has integrated quantitative regression with qualitative process tracing.[62] It has also addressed positive-results bias in Qualitative Comparative Analysis[63] and structured mixed-methods joint displays for contentious political expression.[64] Our qualitative strand draws on these advances. It applies abductive digital-ethnographic coding to de-identified Indonesian youth posts on X and TikTok and sorts them into five recurring socio-technical repertoires (R1–R5; Section 3.3). Tier 4 then calibrates all N = 24 empirical mobilization regimes into exact Ragin four-value fuzzy sets (0.00, 0.33, 0.67, 1.00).[65] These regimes comprise all 20 BERTopic X protest topic clusters (M01–M20)[66] and four macro cross-platform waves: M21 Aug 2024 #KawalPutusanMK, M22 Feb 2025 #IndonesiaGelap Wave 1, M23 Jan–Feb 2025 #KaburAjaDulu Exit Wave, and M24 2025 TikTok MBG Nested Reply Contention. Five conditions are calibrated. ALGO_TACTICS is a coded algospeak, hashtag, or typographic visibility repertoire. BRIDGE_BROKER is the scale-weighted number of communities reached per user, cpu * min(1, n_posts/300), which prevents 2-tweet micro-threads from inflating per-user ratios. MORAL_GRIEVANCE contrasts inclusive human/civic justice framing with ad-hominem vitriol. CONNECTIVE_VOICE contrasts sustained public collective claim-making with disconnective withdrawal or fragmented chatter. POROUS_DELIB captures cross-cutting inter-cluster porosity. The outcome CROSS_CUTTING_REACH is calibrated strictly on empirical quartiles of macro community reach_pct (Q25 = 3.45%, Q50 = 5.95%, Q75 = 11.40%). Conservative Quine–McCluskey minimization is then run for both CROSS_CUTTING_REACH and ~CROSS_CUTTING_REACH, using only observed configurations (no logical remainders), with consistency >= 0.80 and PRI >= 0.65. Two features of the design limit the fsQCA. BRIDGE_BROKER, POROUS_DELIB, and the outcome all derive from cross-community edges, and M21–M24 come from datasets whose community denominators differ from the 1,667 communities used for M01–M20. Regime M01 is the BERTopic outlier bin (topic −1), which is not a thematic topic.

3. Results

3.1. Tier 1: OONI network-interference telemetry

Table 1 and Figure 1 place Indonesia's digital contention infrastructure inside a seven-polity Asian and Global South comparative benchmark. The benchmark rests on 14,428 daily-test OONI records from May 2024 – October 2025. Across the region (Table 1, Panel A; Figure 1A), state network control falls into three distinct regimes. Myanmar sits at the authoritarian extreme. Its military junta enforces pervasive packet-level censorship, with 24.86% web interference across 1,090,718 probes. It also blocks 63.33% of encrypted instant-messaging (Telegram/WhatsApp) tests and 38.34% of Psiphon circumvention tests. The second regime is crisis-triggered internet blackouts. Bangladesh illustrates it during the July–August 2024 student Monsoon Uprising: web interference rose 3.6-fold, from a 3.63% non-uprising baseline to 12.99% during the July 15 – August 6 crackdown (Figure 1A inset). Kenya illustrates it as well, during the June 2024 #RejectFinanceBill youth protests (5.09% anomalies; 2.97% IM anomalies). Indonesia occupies a third, hybrid 'selective-filtering' regime. Its chronic web interference rate is 8.93%, the second highest in the seven-polity panel. That figure combines 4.56% confirmed statutory DNS/HTTP blocks, primarily targeting gambling, adult, and select banned portals, with 4.37% unconfirmed network anomalies across 6,302,732 comparative-window probes. Everyday encrypted-messenger blocking, by contrast, stays low (0.68% overall).

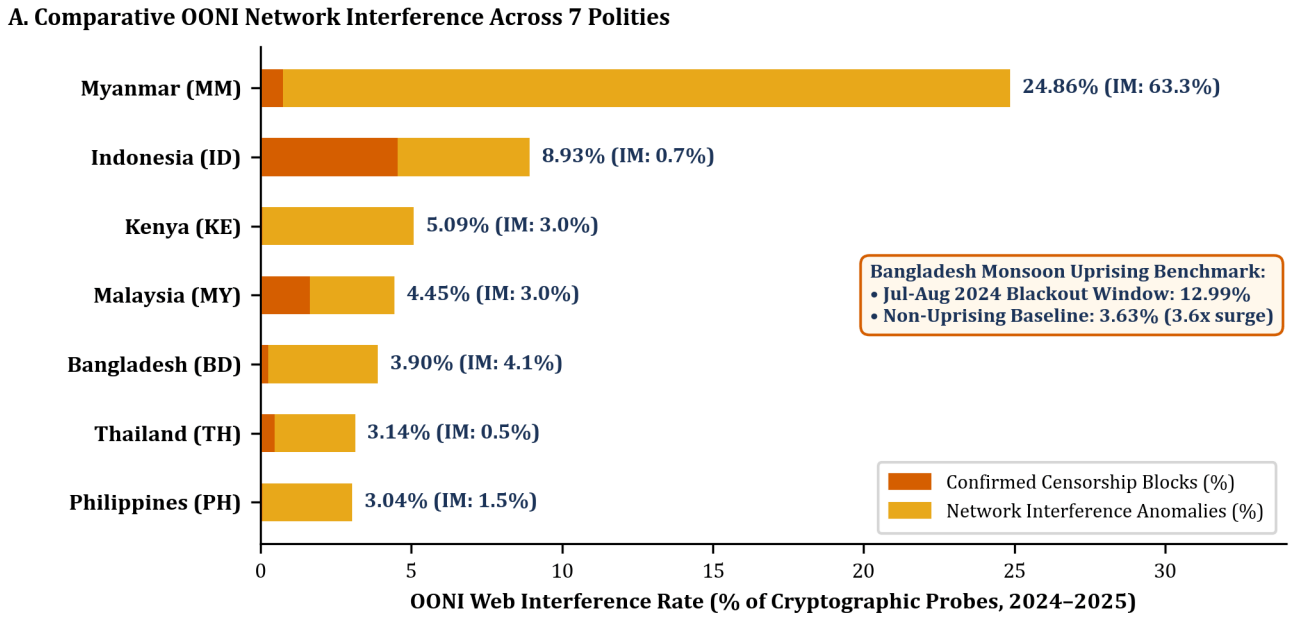
The daily OONI series for Indonesia covers 1,002 days, from January 2023 through October 2025, and totals 10,068,658 web probes (Table 1, Panel B; Figure 1B). A socio-technical pattern appears, but it differs by wave. With year fixed effects and HC3 standard errors, the pooled protest-window coefficient for daily citizen OONI censorship-monitoring probes is +0.268 log units (SE = 0.125, p = 0.0317). Volume rose from 9,563.7 probes/day on baseline days to 11,827.5 probes/day during Wave 1 (August 2024 #KawalPutusanMK), and Wave 3 (August–September 2025 DPR and Affan Kurniawan unrest) went further. It climbed 3.73-fold to 35,701.8 probes/day. Wave 2 (February 2025 #IndonesiaGelap), in contrast, averaged 4,838.1 probes/day, below the baseline (Table 1, Panel B). A change in testing behavior may explain the Wave 3 gap. Citizens and digital-rights watchdogs may use street protests to test thousands of live news, X, TikTok, and streaming URLs instead of static blocked domains. Such a shift would inflate the denominator and lower the static block percentage (−1.457 pp, p = 1.18×10^{-09}), although Wave 2 also shows a lower block percentage with fewer probes. Anomaly rates for encrypted instant messengers (Telegram/WhatsApp/Signal) are slightly higher in every protest wave, from 2.11% at baseline to 2.61% (Wave 1), 2.68% (Wave 2), and 2.71% (Wave 3), but the pooled slope is small and not statistically significant (+0.317 pp, SE = 0.312, p = 0.309). Youth may respond to anticipated throttling and surveillance by diversifying platforms and adopting coded visibility tactics, but the OONI data do not measure youth platform choices.

The contrast between chronic statutory filtering and protest-window vigilance suggests how network-layer governance operates during protest.[48,67,68] Myanmar's military junta severs 63.33% of encrypted instant-messaging connections and 24.86% of web traffic in our OONI data, consistent with the communicative isolation described in the literature,[12] and Bangladesh saw an emergency spike of 12.99% in the July 2024 blackout. Indonesia is different here. Its telecom governance rests on everyday DNS/SNI filtering (8.93% overall web interference), paired with what may be subtle, localized mobile-bandwidth degradation around parliamentary rally perimeters and live-stream endpoints. Young Indonesian demonstrators cannot be certain whether delayed video uploads or failing X/TikTok live streams come from tower congestion or from deliberate throttling. Uncertainty may drive action. In August–September 2025, daily OONI probe execution multiplied nearly fourfold, which is consistent with bottom-up telemetry auditing during protest. Pre-emptive migration toward Signal, Telegram, and VPN circumvention may have accelerated at the same time, but this is not measured here.

Table 1. OONI Network-Interference Measurements Across 7 Youth-Protest Polities (2024–2025) and Indonesia's 1,002-Day Mobilization Event-Window Regressions (Tier 1).

Polity / Contention Window	Temporal / Probe Scope	Web Confirmed Blocks (%)	Web Anomalies (%)	Total Web Interf. (%)	Encrypted IM / Circumvention Telemetry & Statistical Test
Panel A: Comparative Asian & Global South Youth-Protest Polities (OONI REST API v1, May 2024 – Oct 2025)					
Myanmar (MM — Junta Firewall)	1,090,718 probes	0.75%	24.11%	24.86% (#1)	IM anomalies: 63.33% | Psiphon: 38.34%
Indonesia (ID — Selective Filtering)	6,302,732 probes	4.56%	4.37%	8.93% (#2)	IM anomalies: 0.68% | Psiphon: 3.60%
Kenya (KE — #RejectFinanceBill)	5,531,361 probes	0.01%	5.08%	5.09%	IM anomalies: 2.97% | Unannounced ISP throttling
Malaysia (MY — DNS/Web Filtering)	10,114,757 probes	1.65%	2.80%	4.45%	IM anomalies: 3.00% | Psiphon: 1.81%
Bangladesh (BD — Monsoon Uprising)	3,162,962 probes	0.26%	3.64%	3.90%	Jul–Aug 2024 Blackout Surge: 12.99% vs. 3.63% baseline (3.6×)
Thailand (TH) & Philippines (PH)	4.46M & 3.68M probes	0.48% / 0.00%	2.66% / 3.04%	3.14% / 3.04%	IM: 0.51% (TH) & 1.46% (PH); PH mobile TLS middlebox timeout
Panel B: Indonesia 1,002-Day OONI Telemetry Across 3 Hybrid Youth Contention Waves (Jan 2023 – Oct 2025)					
Baseline Non-Protest Days	n = 952 days (9,563.7/day)	5.74%	4.45%	10.20%	Encrypted IM anomaly baseline: 2.11% (Telegram/WA/Signal)
Wave 1: Aug 2024 #PeringatanDarurat	n = 15 days (11,827.5/day)	5.08%	4.01%	9.10%	IM anomaly rate rises to 2.61% (+0.50 pp); +23.7% probe volume
Wave 2: Feb 2025 #IndonesiaGelap	n = 15 days (4,838.1/day)	3.21%	2.86%	6.07%	IM anomaly rate rises to 2.68% (+0.57 pp) amid #KaburAjaDulu
Wave 3: Aug–Sep 2025 DPR/Affan Unrest	n = 20 days (35,701.8/day)	3.27%	3.70%	6.98%	3.73× citizen OONI probe surge; IM anomaly rate hits 2.71%
HC3 Event-Window Regressions (Year FE)	N = 1,002 daily obs.	Log Probe Volume: +0.268*	SE = 0.125 (p = 0.0317)	Block Ratio: −1.457***	IM Anomaly Slope: +0.317 pp (SE = 0.312, p = 0.309)

Notes: Compiled from Official OONI REST API v1 (5,010 Indonesian daily-test rows covering 10,068,658 web measurements, 542,119 confirmed blocks, and 448,364 anomalies across 2023–2025; plus 14,428 comparative daily-test rows across 7 polities). The pooled protest-window coefficient of +0.268 log in probe volume (p = 0.0317) coincides with a lower static-block share; the pooled term combines Wave 1 (+24%), Wave 2 (−49%), and Wave 3 (+273%) relative to baseline. Relative to the 9,563.7 probes/day baseline, probe volume was +23.7% in Wave 1, −49.4% in Wave 2, and +273% in Wave 3. Wave 1 spans #PeringatanDarurat and #KawalPutusanMK (August 2024).



B. Indonesia 1,002-Day OONI Telemetry Across 3 Protest Waves

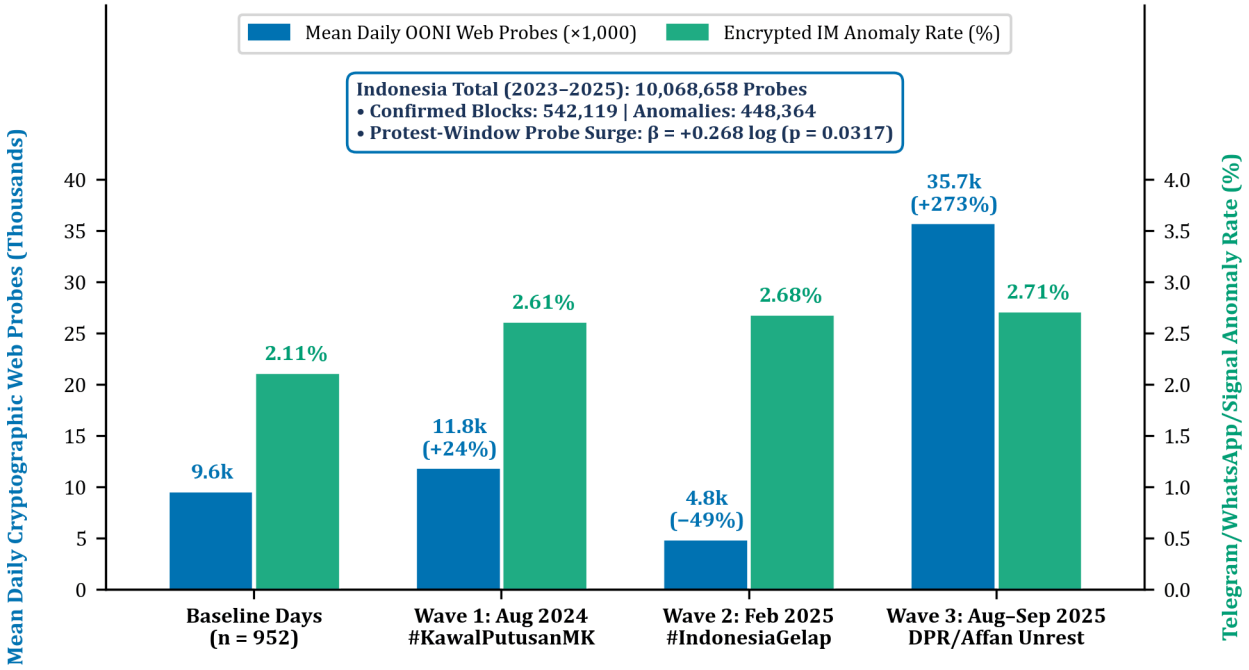


Figure 1. OONI Network-Interference Measurements and Citizen Censorship-Monitoring Volume (Tier 1: Official OONI REST API v1). Panel A compares web confirmed censorship blocks and network interference anomalies across seven Asian and Global South youth-protest polities (May 2024 – October 2025: Myanmar 24.86% web / 63.33% IM; Indonesia 8.93%; Kenya 5.09%; Malaysia 4.45%; Bangladesh 3.90% overall, surging 3.6× from 3.63% to 12.99% during the July–August 2024 uprising; Thailand 3.14%; Philippines 3.04%). Panel B tracks Indonesia's 1,002-day OONI telemetry (10,068,658 web measurements, 2023–2025) across Baseline Days (9.6k probes/day; 2.11% IM anomalies) versus Wave 1 (Aug 2024 #KawalPutusanMK: 11.8k/day; 2.61% IM), Wave 2 (Feb 2025 #IndonesiaGelap & #KaburAjaDulu: 2.68% IM), and Wave 3 (Aug–Sep 2025 DPR/Affan Unrest: 35.7k probes/day, pooled HC3 protest-window log coefficient β = +0.268, p = 0.0317; 2.71% IM anomalies).

3.2. Tier 2: Protest topology on X, grassroots bridge brokers, RIF quantiles, and moral-shock porosity

Tables 2–3 and Figures 2–3 dissect how connective protest narratives diffuse across structurally fragmented X communities. The network holds 29,289 tweets, 13,994 directed edges, and 11,426 nodes, partitioned into 1,667 Louvain communities. State officials often dismiss such mobilization as elite-driven 'astroturf', yet the data point the other way. Ordinary grassroots citizens make up 97.93% of all protest network participants (11,189/11,426 nodes). Institutional news media (120 nodes; 1.05%) and political elites (117 nodes; 1.02%) together account for barely two percent (Table 2, Panel A). Of all cross-community Diffusion Drivers, 99.21% (1,002 of 1,010 bridge brokers) are non-elite grassroots accounts. Two other groups behave very differently. Local Amplifiers number 6,163 (53.94% of nodes), post only inside their home Louvain cluster (0.00% outward cross-community ties), and average just 1,360.0 cumulative views, while Attention Sinks number 4,253 (37.22% of nodes) and include major news outlets averaging 97,765.4 views and 18.74 incoming ties. They absorb @mentions passively and never initiate outward bridges (0.00% outward cross-ties). Grassroots Diffusion Drivers, in contrast, send 42.76% of their outgoing ties across community boundaries and reach an average of 1.75 external Louvain communities. They also generate 14,121.8 mean views, a 10.4-fold ratio of mean views relative to siloed Local Amplifiers (Figure 2A).

Doubly Robust AIPW and RIF unconditional quantile regressions (Table 3; Figure 3) describe the adjusted and distributional pattern of this grassroots brokerage. Among active protest initiators (N = 7,170), cross-community Diffusion Drivers show cumulative actor visibility that is higher by +1.0318 log view units after adjustment (SE = 0.0744, z = 13.86, $p < 1 \times 10^{-43}$; VanderWeele E-value = 2.28, Cinelli–Hazlett RV_q = 15.1%). Across all N = 7,583 posting actors (Table 3, Panel B; Figure 3A), RIF quantile slopes show a structural division of labor. Bridge Brokerage is null at the zero-view Q10 floor (−0.067, p = 0.343), then climbs sharply at Q25 (+0.260, p = 0.0346) and Q50 (+0.430, $p = 1.17 \times 10^{-06}$), and is largest at Q75 (+0.450, p = 0.00017), although the Q50 and Q75 estimates do not differ appreciably. At the Q90 mega-viral tail it is smaller and not significant (+0.293, p = 0.138), while log in-degree centrality rises to +2.446 ($p = 7.49 \times 10^{-37}$). The tweet level tells a similar story. Across N = 29,289 tweets, Quote-Framing Visibility Tactics appear in 11.47% of posts and 18.53% of network edges. Youth use them to 'quote-dunk' official statements or to translate eyewitness clips across clusters. Tweets that use them show visibility that is higher by +1.5722 log views after adjustment (AIPW SE = 0.0457, z = 34.37, $p < 1 \times 10^{-250}$, E-value = 2.70, RV_q = 18.2%).

High volume does not automatically mean integration across communities (Table 2, Panel B; Figure 2B). Take general parliamentary outrage ('*Demo* & DPR'), with 2,482 tweets and 41.0% community penetration. It shows the lowest inter-community cross-edge ratio in the whole corpus: 6.4%, so 93.6% of its interactions fall inside Louvain communities (CFI = −0.280). Human moral shock behaved differently. The death of 21-year-old ride-hailing driver Affan Kurniawan produced the deepest multi-hop diffusion cascade in the network (max_hop = 7, mean hop = 2.84), with 6,790.9 mean post-shift engagements/tweet and the Rank #1 Cognitive Fusion Index = +0.524. It also coincided with an +85.3% network-wide rise in Louvain cross-community porosity, from 0.0516 pre-shift to 0.0956 post-shift (Welch t = 3.030, p = 0.0029; Mann–Whitney p = 0.0024). The pre/post comparison involves different sets of active communities (113 and 81) and does not weight communities by size. The cross-edge ratio of the Affan

Kurniawan stream (13.7%) ranks fifth of the seven narrative streams (Table 2, Panel B).

Two earlier Indonesian benchmark waves (Table 2, Panel A) offer a comparison. Set against them, the August–September 2025 dynamics are consistent with a maturation of youth tactical brokerage, which is our own inference from Table 2; compare work on temporal shifts in tactics and on knowledge transmission.[9,15] The first wave was the August 2024 #KawalPutusanMK / Blue Garuda emergency mobilization (1,567 benchmark tweets). The second was the February 2025 #IndonesiaGelap student austerity wave: 3,054 tweets across 2,364 nodes and 2,998 directed edges, averaging 56.28 likes, 17.88 retweets, and a 42.57% conversational reply share. In both, university student councils, constitutional-law collectives, and K-pop/anime fandom communities built reusable cross-cluster quote-amplification routines. The August–September 2025 parliamentary allowance and police-violence crisis then erupted. Those grassroots Diffusion Drivers re-activated fast across 1,667 Louvain communities. This helps explain why Movement/Hashtag coordination ('*Gerakan*/Hashtag': 20.5% cross-edge ratio) and explicit Political Demands ('*Politik & Tuntutan*': 24.7% cross-edge ratio) held inter-community bridging ratios 3.2 to 3.9 times higher than generic reactive anger ('*Demo* & DPR': 6.4%).

Table 2. Multi-Wave X (Twitter) Connective Protest Network Topology, Structural Actor Brokerage, Moral-Shock Porosity Shift, and 7-Narrative Cognitive Fusion Profiles in Indonesia (Tier 2).

Network Stratum / Protest Narrative	Nodes / Posts	Share / Reach (%)	Cross-Community Bridging	Engagement / Cascade Depth	Topological & Cognitive-Fusion Role
Panel A: Actor Structural Roles & Account Strata Across Aug–Sep 2025 Protest Network (N = 11,426 Nodes; 1,667 Communities)					
Diffusion Drivers (Bridge Brokers)	n = 1,010 (99.21% grassroot)	8.84% of nodes	1.75 comm. (42.76% cross-out)	14,121.8 mean views (4.72 tweets)	10.4× higher views than Local Amplifiers; inter-silo bridges
Local Amplifiers (Intra-Silo Peers)	n = 6,163 (99.69% grassroot)	53.94% of nodes	0.00 comm. (0.00% cross-out)	1,360.0 mean views (1.38 tweets)	Confined within single Louvain cluster; low external reach
Attention Sinks (Media & Elites)	n = 4,253 (413 posting)	37.22% of nodes	0.00 comm. (0.00% cross-out)	20,556.2 mean views (media: 97.8k)	High in-degree targets (18.7 media, 17.3 elite); zero out-bridging
Moral-Shock Louvain Porosity Shift	Pre (113) vs. Post (81)	0.0516 → 0.0956	+0.0440 (+85.3% jump)	Welch t = 3.030 (p = 0.0029)	Mann–Whitney p = 0.0024; Coincides with the Affan shock
Earlier Benchmark Waves (2024–Feb 2025)	1,567 & 3,054 tweets	2,364 nodes / 2,998 edges	42.57% reply share (Feb 2025)	56.28 likes / 17.88 RTs (Feb 2025)	#KawalPutusanMK (Aug 2024) & #IndonesiaGelap Wave 1
Panel B: Seven Core Protest Narratives — Community Penetration, Cascade Hop Depth & Cognitive Fusion (Aug–Sep 2025)					
1. Affan Kurniawan (Gig-Worker Martyr)	743 tweets / 479 users	6.1% (102 comm.)	13.7% cross-edges (0.213/user)	Max Hop = 7 (Avg 2.84); 6,791 eng/tw	Rank #1 Cognitive Fusion (CFI = +0.524); deepest cascade
2. Security & State Response	206 tweets / 158 users	4.1% (68 comm.)	18.4% cross-edges (0.430/user)	Max Hop = 5 (Avg 2.63); 6,240 eng/tw	Rank #2 Cognitive Fusion (CFI = +0.303); high per-user reach
3. Movement & Hashtag Coordination	2,356 tweets / 1,064 users	15.2% (253 comm.)	20.5% cross-edges (597/2,916)	Max Hop = 3 (Avg 1.83); 2,229 eng/tw	Rank #3 Cognitive Fusion (CFI = +0.200); tactical brokerage
4. Political Demands & Reform	1,437 tweets / 1,059 users	7.3% (122 comm.)	24.7% cross-edges (#1 ratio)	Max Hop = 3 (Avg 1.87); 560 eng/tw	Rank #4 CFI (−0.188); highest cross-edge deliberation share
5. Police Violence (*Kekerasan Aparat*)	2,276 tweets / 1,674 users	32.4% (540 comm.)	10.9% cross-edges (225/2,055)	Max Hop = 4 (Avg 1.93); 2,128 eng/tw	Rank #5 CFI (−0.270); broad outrage, moderate siloing
6. Parliamentary Protest (*Demo* & DPR)	2,482 tweets / 1,998 users	41.0% (#1: 683 comm.)	6.4% cross-edges (lowest)	Max Hop = 5 (Avg 2.27); 767 eng/tw	Rank #6 CFI (−0.280); widest volume but 93.6% intra-silo
7. Popular Economy (*Ekonomi Rakyat*)	1,277 tweets / 995 users	9.2% (154 comm.)	14.5% cross-edges (155/1,072)	Max Hop = 4 (Avg 2.00); 1,348 eng/tw	Rank #7 CFI (−0.289); material cost-of-living grievances

Notes: Harmonized from the Indonesia Digital Protest Network Archive of Rahmandika, Ramadhani, and Alamsyah (2026, CC BY 4.0) (29,289 tweets, 13,994 directed edges: 46.43% mention, 35.04% reply, 18.53% quote; 3,966 cascade hop nodes) after rectifying the upstream '@' handle prefix to link 7,583 active posting actors (31,130,601 cumulative views), plus Feb 2025 #IndonesiaGelap SNA and Jul–Aug 2024 #KawalPutusanMK archives. The Attention Sink mean (20,556.2 views) refers to the 413 posting sinks; with this convention the three groups add up to the 31,130,601 cumulative views.

Table 3. Doubly Robust AIPW Causal Estimates and Firpo–Fortin–Lemieux RIF Unconditional Quantile Regressions of Protest Visibility Reach on X (Tier 2: N = 7,583 Posting Actors & N = 29,289 Tweets).

Econometric Estimand / Unconditional Quantile	Sample Scope	Point Estimate (ATE / β)	Bootstrap / HC3 SE	95% CI / Covariate Balance	p-Value & Unobserved-Confounding Bounds
Panel A: Doubly Robust Augmented Inverse-Probability Weighting (AIPW) Visibility Models on X					
AIPW 1: Grassroots Bridge Brokerage (Diffusion Driver vs. Local Amplifier) → Log Actor Views	N = 7,170 (1,010 vs. 6,160)	+1.0318 log	(0.0744)	[0.8859, 1.1777] | z = +13.86	$p < 1 \times 10^{-43}$ | E-value = 2.28 (CI 2.13), RV_q = 15.1%
AIPW 2: Quote-Framing Visibility Tactic (Quote vs. Standard Post/Reply) → Log Tweet Views	N = 29,289 (3,358 vs. 25,931)	+1.5722 log	(0.0457)	[1.4825, 1.6618] | z = +34.37	$p < 1 \times 10^{-250}$ | E-value = 2.70 (CI 2.60), RV_q = 18.2%
Panel B: RIF Unconditional Quantile Regressions of Log Actor Cumulative Views (N = 7,583 Active Posting Nodes)					
Q10 Floor (q_0.10 = 0.00)	N = 7,583 Actors	Bridge: −0.0671	(0.0707)	In-Degree: −0.3165***	Bridge p = 0.343 (ns at zero-view floor)

Econometric Estimand / Unconditional Quantile	Sample Scope	Point Estimate (ATE / β)	Bootstrap / HC3 SE	95% CI / Covariate Balance	p-Value & Unobserved-Confounding Bounds
Q25 Lower-Middle (q_0.25 = 3.04)	N = 7,583 Actors	Bridge: +0.2595*	(0.1228)	In-Degree: −0.2751**	Bridge p = 0.0346; grassroots bridging emerges
Q50 Median Reach (q_0.50 = 4.49)	N = 7,583 Actors	Bridge: +0.4297***	(0.0883)	In-Degree: +0.2531***	Bridge p = 1.17×10^{-06}; bridge coefficient at the median
Q75 Upper-Middle (q_0.75 = 5.95)	N = 7,583 Actors	Bridge: +0.4504***	(0.1196)	In-Degree: +0.8964***	Bridge p = 0.00017 (largest bridge coefficient)
Q90 Viral Hub Tail (q_0.90 = 7.43)	N = 7,583 Actors	Bridge: +0.2934	(0.1980)	In-Degree: +2.4461***	Bridge p = 0.138; in-degree term dominates Q90 (p = 7.5×10^{-37})

Notes: Panel A AIPW propensity scores estimated via IRLS logistic regression clipped to [0.05, 0.95] controlling for grassroots status, log followers, log in-degree, verification, and coded algospeak markers (present in 20.91% of tweets). Panel B includes all 7,583 active posting nodes (including passive media/elite Attention Sinks) controlling for grassroots status, log tweet volume, and log in-degree centrality with HC3 SEs. Posting volume (tweets per actor) is not a covariate in Panel A (AIPW 1).

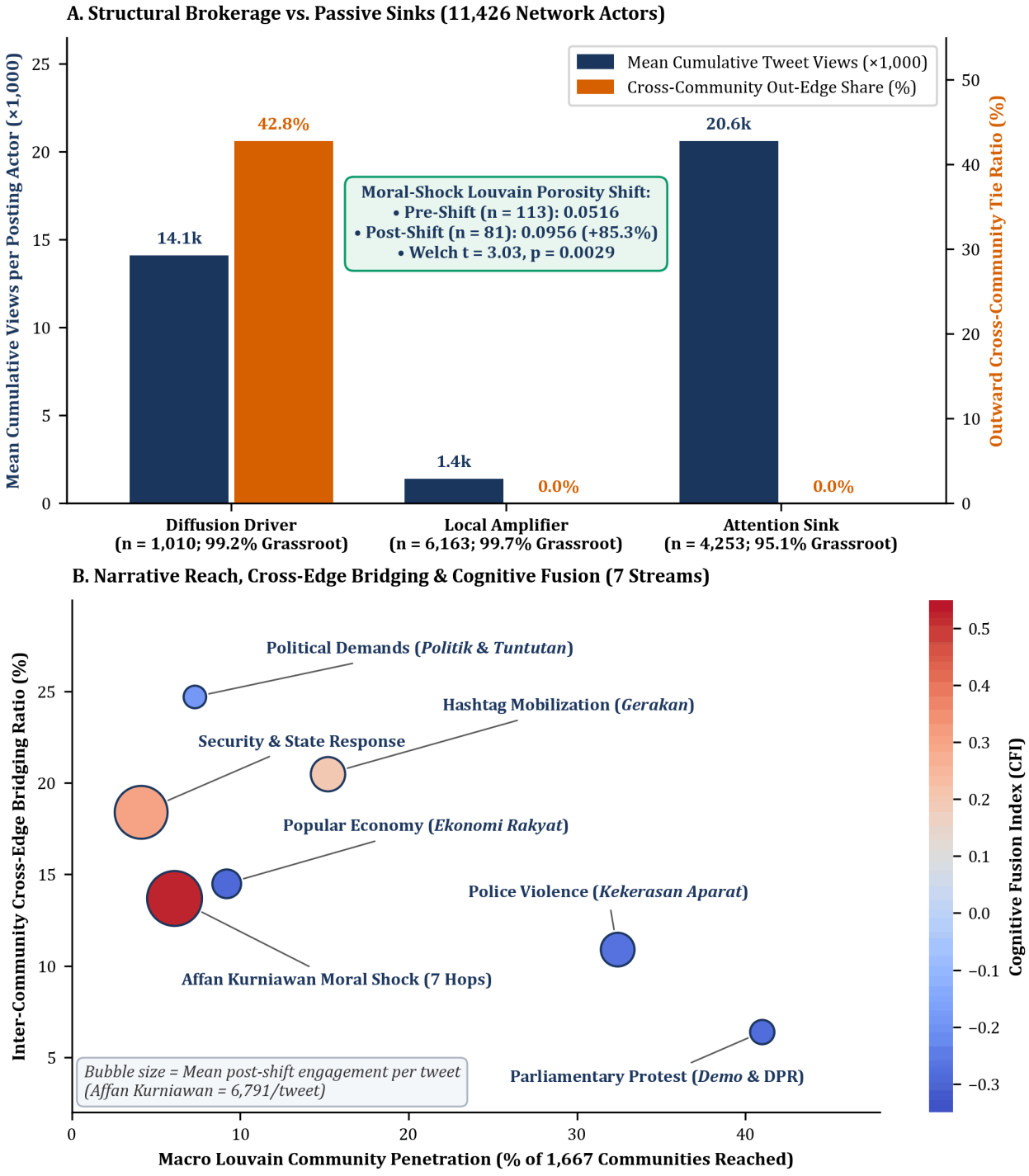


Figure 2. Multi-Wave Connective Protest Network Topology, Grassroots Bridge Brokerage, and Moral-Shock Porosity on X (Tier 2: N = 11,426 Network Actors; 1,667 Louvain Communities). Panel A contrasts cumulative tweet views and outward cross-community tie shares across Diffusion Drivers (n = 1,010; 99.2% grassroot; 14.1k mean views; 42.8% cross-community ties), Local Amplifiers (n = 6,163; 1.4k views; 0.0% cross-ties), and passive Attention Sinks (n = 4,253; 20.6k views; 0.0% cross-ties), alongside the +85.3% post-moral-shock jump in Louvain community porosity (0.0516 to 0.0956, Welch t = 3.03, p = 0.0029). Panel B maps all seven protest narrative streams across macro community penetration (%), cross-edge bridging ratio (%), post-shift engagement per tweet (bubble size), and Cognitive Fusion Index (CFI).

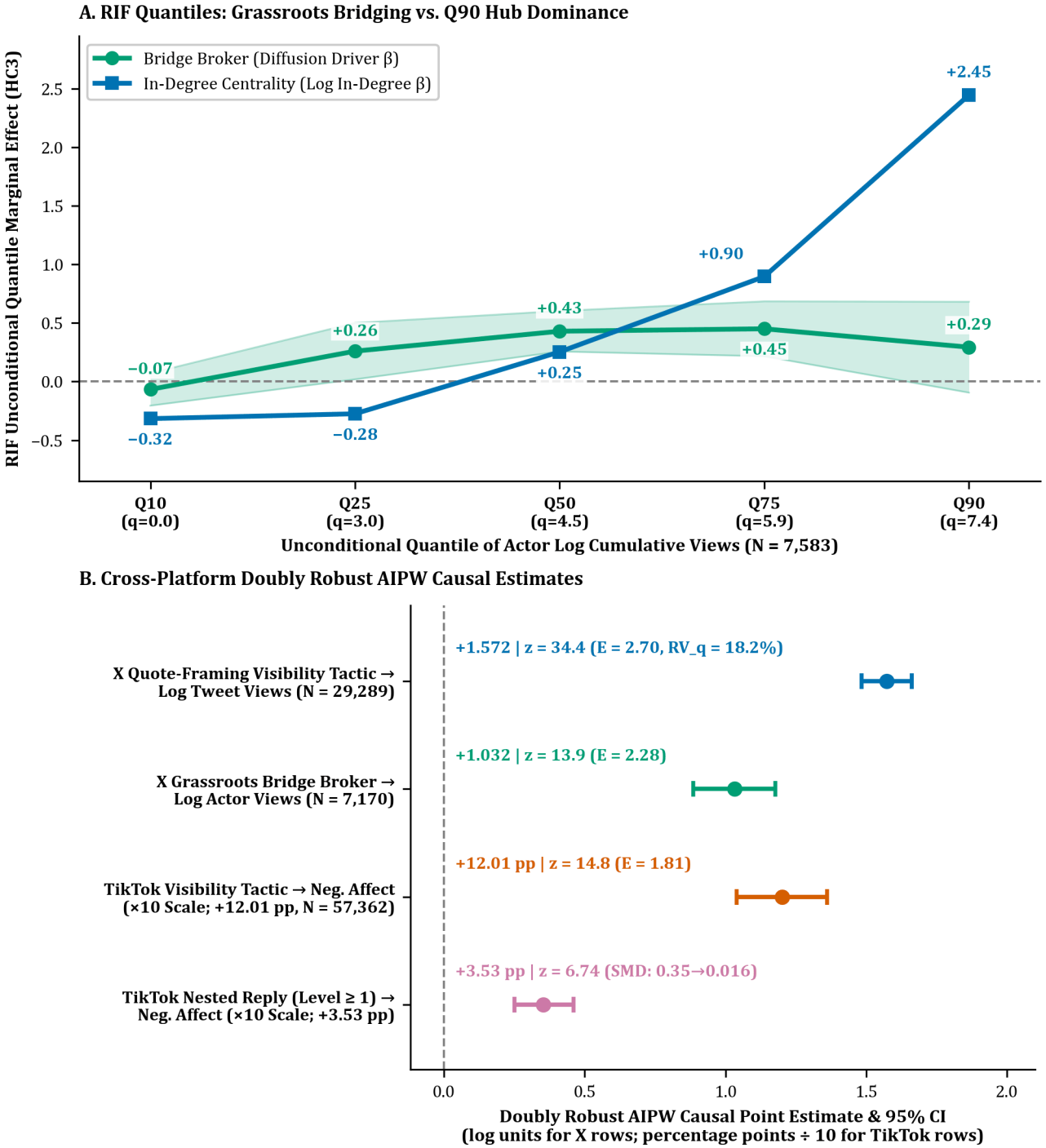


Figure 3. Distributional RIF Quantiles of Protest Visibility and Doubly Robust AIPW Cross-Platform Effects (Tiers 2 & 3). Panel A plots Firpo–Fortin–Lemieux RIF unconditional quantile slopes (Q10–Q90) across 7,583 active posting X protest nodes, showing that the Grassroots Bridge Brokerage coefficient is largest across Q50 (+0.430, $p = 1.17 \times 10^{-06}$) and Q75 (+0.450, p = 0.00017) whereas log in-degree centrality dominates at Q90 (+2.446, $p = 7.49 \times 10^{-37}$). Panel B presents Doubly Robust AIPW estimates with 95% confidence intervals, VanderWeele E-values, and Cinelli–Hazlett RV_q bounds across X and TikTok.

3.3. Tier 3: #KaburAjaDulu exit, TikTok nested replies, and ethnographic repertoires

Tables 4–5 and Figure 4 examine what happens when youth contention moves across action modes and across algorithmic video architectures. Two cases are compared. The first is #KaburAjaDulu, a disconnective exit on X (N = 4,768 unique posts), and the second is TikTok MBG nested reply threads (N = 57,362 comments), supplemented by 9,882 human-validated TikTok Indonesia comments. In #KaburAjaDulu (Table 4, Panel A; Figure 4A), 61.39% of labeled posts express pointed disillusionment with domestic governance and labor conditions. A further 24.97% share neutral-informational migration logistics. Frames matter here. Frame disaggregation shows that practical overseas visa, scholarship, and skill-exit tutorials (covering Japanese nursing/specified-skilled visas, German Ausbildung, and Australian Working Holiday Visas) reach 151.84 mean likes and 22.08 retweets. This is 6.2 times the engagement of pure domestic wage/tax complaint posts (24.68 likes). Overlap exists too: 8.54% of #KaburAjaDulu posts explicitly co-deploy #IndonesiaGelap or #PeringatanDarurat. So disconnective exit and connective protest may operate as intertwined repertoires and not as mutually exclusive camps,[2,3] although the 8.54% overlap is reported without a baseline. The hashtag also draws fierce affective counter-framing. Threads debating filial caregiving guilt, and nationalist accusations of 'unpatriotic desertion', generate the highest conflict virality at 172.30 mean likes and 27.19 retweets. These means are not accompanied by

medians or intervals, and engagement counts are heavy-tailed.

On TikTok (Table 4, Panels B–C; Figure 4B), algorithmic interest clustering[22,69] and nested comment-tree design may intensify negative sentiment. Of all 57,362 MBG policy comments, 61.62% register 4-model consensus negative sentiment. A further 47.97% receive mixed polarity labels from the four classifiers (a 'pragmatic split'), which may reflect youth irony, slang, and formatting satire; irony was not coded separately. Doubly Robust AIPW estimates that, relative to top-level video comments (level 0: 60.79% negative), Nested Reply-Tree Sub-Threads (level >= 1: 18.19% of comments; 65.34% negative) have consensus negativity that is higher by +3.53 percentage points after adjustment (SE = 0.52 pp, z = 6.74, $p = 1.57 \times 10^{-11}$). IPTW max |SMD| fell from 0.3532 to 0.0159, well below the 0.05 balance benchmark. Comment-level Typographic and Coded Visibility Tactics (ALL-CAPS emphasis, punctuated rhetorical demands, and oppositional code words) are associated with negative consensus that is higher by +12.01 pp (AIPW z = 14.77, $p < 1 \times 10^{-48}$, E-value = 1.81). A separate 9,882-comment human-linguist TikTok benchmark points in the same direction. There, visibility tactics occur in 18.90% of comments and are associated with human-coded negativity that is higher by +9.05 pp (39.67% to 48.72%). The tactic coding is the same, and the baseline negativity is about 21 pp below the classifier rate. Active hourly TikTok contention threads (Figure 4B) show a tail crossover in RIF quantile regressions. Nested Reply-Tree Share is associated with higher thread negativity at Q10 (+19.38 pp, p = 0.0346) and Q25 (+22.74 pp, $p = 8.41 \times 10^{-05}$), and its slope is largest at the median Q50 (+37.70 pp, $p = 1.46 \times 10^{-05}$). At the Q90 pile-on tail (80.65% negativity), the slope for the share of Typographic/Algospeak Visibility Tactics is largest (+60.86 pp, p = 0.0235). The Q90 estimate is one of ten quantile tests and was not corrected for multiplicity.

Table 5 summarizes our abductive digital-ethnographic coding of five youth socio-technical repertoires (R1–R5) across X and TikTok. R1 is Connective Moral-Shock Witnessing around Affan Kurniawan's death. R2 is Coded Numerical and Orthographic Algospeak. Three examples follow: '1312' (reaching 0.456 communities/user on X), 'Konoha/Wakanda' state aliases, and vowel-dropped TikTok tax-strike calls ('*sbaiknya kt mogok masal jng byar pjak*').[29,30] R3 is Ironic UI/Typographic FYP Satire, such as mocking an official's tone through word-processor commands ('*ibuk ngomongnya, TIMES NEW ROMAN, BOLD, CAPLOCK NYALA, 16, CTRL + E*'), and literal NLP sentiment classifiers split on these comments (2 neutral vs. 2 negative) even though the comments still capture top-comment placement. R4 is Disconnective Transnational Skill-Exit. It takes the form of '#KaburAjaDulu' comparative wage tables and visa mentorship. Last comes R5: Nested Reply-Tree Antagonism and Cyber-Troop ('Buzzer') Counter-Framing.[45–47]

Comparing R2, R3, and R4 closely suggests the semiotic agility of Indonesian Gen-Z and millennial participants. Conventional ideological manifestos are easily buried by algorithmic down-ranking, and they can be targeted under Indonesia's Electronic Information and Transactions Law (UU ITE). So youth may weave critique into everyday digital vernaculars, including coded language.[18,29,70,71] On TikTok, audio-visual clips of officials defending budget cuts or MBG meal logistics circulate across millions of FYP feeds. Top-ranked youth comments there use deadpan workplace and software humor ('*ENTER ENTER ENTER Langsung ke INTI nya*' or '*TIMES NEW ROMAN, BOLD, CAPLOCK NYALA*'). The humor punctures bureaucratic authority. No flagged profanity is needed. In #KaburAjaDulu threads on X, the pattern differs: spreadsheets compare a Rp 20 million monthly blue-collar wage in Japan or South Korea with domestic sub-living minimum wages, and they set both against arbitrary 'maximum age 25, good-looking' job advertisements. Private labor-market humiliation may become shared generational solidarity, which could explain why informational exit threads draw sixfold higher peer endorsement than isolated complaints.

Table 4. Cross-Platform Disconnective Exit (#KaburAjaDulu) Frame Metrics and TikTok Nested Reply-Tree Negative-Sentiment AIPW & RIF Quantile Estimates (Tier 3: N = 4,768 X Posts; N = 57,362 & 9,882 TikTok Comments).

Analytical Panel / Frame / Quantile	Sample Scope	Prevalence / Baseline	Estimate (Likes / ATE / β)	SE / Secondary Metric	p-Value & Substantive Mechanism
Panel A: #KaburAjaDulu ('Just Escape First') Disconnective Youth Exit Frames on X (N = 4,768 Unique Posts)					
Visa, Overseas Scholarships & Skill-Exit Tutorials	n = 422 core threads	8.85% of corpus	151.84 mean likes	22.08 mean RTs	6.2× higher likes than complaint-only posts; mutual-aid logistics
Connective–Disconnective Crossover (#IndonesiaGelap)	n = 407 bridge posts	8.54% of corpus	44.00 mean likes	12.96 mean RTs	Explicitly fuses street protest grievances with exit tutorials
Domestic Wage Precarity, Tax & Job-Age Caps	n = 204 explicit posts	4.28% of corpus	24.68 mean likes	4.14 mean RTs	Critiques informal precarity, punitive taxes & ageist hiring
Family Caregiving Guilt & Patriotic Counter-Shaming	n = 163 contested posts	3.42% of corpus	172.30 mean likes (#1)	27.19 mean RTs	Intense affective clash over 'nationalist loyalty' vs. survival
Panel B: TikTok Nested Reply-Tree Contention (N = 57,362 MBG Comments) & Human-Coded Benchmark (N = 9,882)					
AIPW 1: Nested Reply-Tree (Level ≥ 1 vs. Level 0) → Negativity	N = 57,362 (18.19% nested)	60.79% → 65.34% raw	+3.53 pp (z = +6.74)	SE = 0.52 pp | SMD: 0.35→0.016	$p = 1.57 \times 10^{-11}$ | E-value = 1.34; dyadic sub-thread hostility
AIPW 2: Visibility Tactics → Negative Affective Consensus	N = 57,362 (8.36% tactic)	60.84% → 72.85% adj.	+12.01 pp (z = +14.77)	SE = 0.81 pp | E = 1.81	$p < 1 \times 10^{-48}$ | Checked in the human-coded TikTok benchmark (+9.05 pp: 39.67→48.72%)
AIPW 3: Overt Oppositional Tactics → 4-Model Classifier Split	N = 57,362 (47.97% split)	48.79% → 43.31% adj.	−5.48 pp (z = −5.75)	SE = 0.95 pp | E = 1.45	$p = 8.75 \times 10^{-09}$; UI/ironic satire splits models (48%), overt caps unify neg.

Analytical Panel / Frame / Quantile	Sample Scope	Prevalence / Baseline	Estimate (Likes / ATE / β)	SE / Secondary Metric	p-Value & Substantive Mechanism
Panel C: TikTok Hourly Contention-Window RIF Unconditional Quantile Slopes of Negative Sentiment (%)					
Q10 (50.00%) & Q25 (56.68%) Thread Windows	Active Video×Hour Threads	Moderate Contention	Nested: +19.38* / +22.74*** pp	Tactic: −0.49 / +8.02 pp (ns)	p = 0.0346 (Q10) & p = 8.41×10^{-05} (Q25); sub-threads are associated with more negativity
Q50 Median (63.97%) & Q75 (73.36%) Windows	Active Video×Hour Threads	High Contention	Nested: +37.70*** / +21.11* pp	Tactic: −20.64 / −11.95 pp (ns)	p = 1.46×10^{-05} (Peak Q50 nested-reply polarization) & p = 0.0459
Q90 Extreme Pile-On Tail (80.65% Negativity)	Active Video×Hour Threads	Hyper-Polarized Tail	Tactic: +60.86* pp	Nested: −6.82 pp (p = 0.380)	p = 0.0235; tactic slope is largest at Q90

Notes: Harmonized across 4,768 unique #KaburAjaDulu posts (4,597 labeled: 61.39% critical/negative, 24.97% neutral-informational, 13.64% positive), 57,362 nested TikTok MBG policy comments scored across 4 NLP classifiers (taufiqdp, agufsamudra, mdhugol, aardiiiiy), and 9,882 human-linguist validated TikTok Indonesia comments. Panel C reports ten quantile tests without correction for multiplicity).

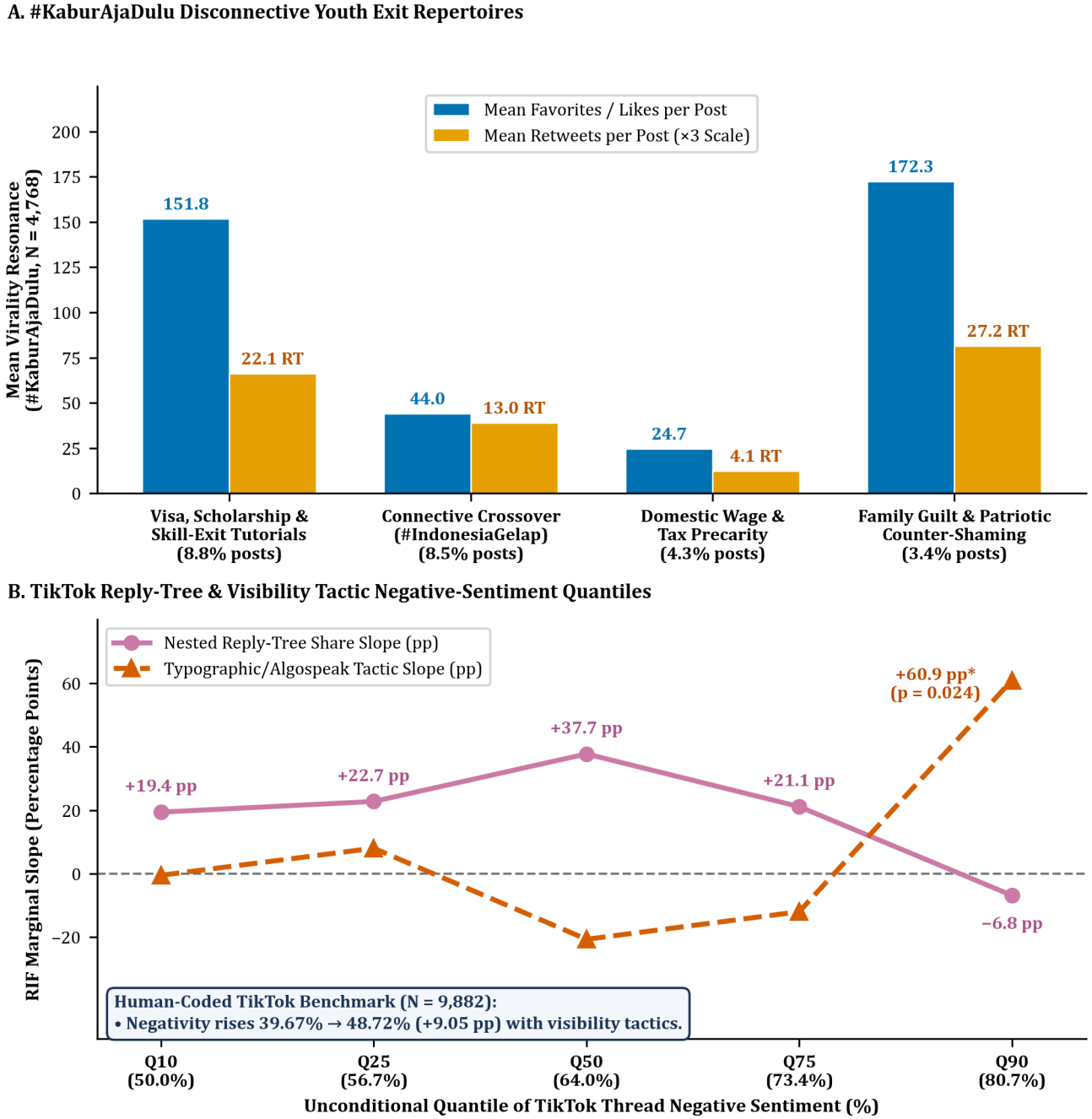


Figure 4. Disconnective Transnational Exit (#KaburAjaDulu) Versus TikTok Nested Reply-Tree Negative Sentiment (Tier 3). Panel A compares mean likes and retweets across four #KaburAjaDulu frames (N = 4,768 unique posts), highlighting high virality for overseas visa/scholarship exit tutorials (151.8 likes) and patriotic counter-shaming clashes (172.3 likes) alongside 8.54% direct crossover with #IndonesiaGelap. Panel B plots RIF unconditional quantile slopes across active TikTok hourly contention windows (N = 57,362 MBG comments) plus the 9,882 human-validated TikTok benchmark, showing Nested Reply-Tree Share with its largest slope (+37.70 pp) at Q50 (p = 1.46×10^{-05}) while Typographic/Algospeak Tactics reach +60.86 pp at Q90 (p = 0.0235, uncorrected for ten tests).

Table 5. Digital Ethnographic Discourse Taxonomy of Five Youth Connective, Visibility-Evasive, and Disconnective Repertoires Across X and TikTok (Tier 3 Qualitative Strand).

Repertoire Code & Sociological Construct	Primary Platform Locus	Empirical Prevalence in Verified Corpora	De-Identified Illustrative Utterance / Archival Anchor	Socio-Technical & Affective Mechanism
R1 Connective Moral Shock Solidarity	X (Twitter) Cascades	Topic 6 ('Affan Kurniawan'): 714 tweets, 298 communities reached (0.497 communities/user; max_hop = 7; CFI = +0.524)	Aug–Sep 2025 Hashed Protest Corpus (Topic 6 / Cascade Hop 1–7)	Concrete human injustice against an ordinary gig-economy worker may puncture partisan silos; Louvain cross-community porosity was +85.3% higher afterward (0.0516 to 0.0956, p = 0.0029).
R2 Coded Algospeak Moderation Evasion	X & TikTok Comments	20.91% of X protest posts & 18.9% of 10K human-validated TikTok comments deploy coded/typographic visibility tactics; Topic 7 ('1312') reaches 0.456 communities/user	10K TikTok #0 ('*sbaiknya kt mogok masal jng byar pjak*...') & Protest Corpus ('indonesiagelap', '1312')	Vowel dropping ('sbaiknya kt jng byar pjak'), numeric codes ('1312'), and state aliases ('Konoha/Wakanda') evade automated keyword demotion while intensifying oppositional negativity (+9.05 pp in 10K human benchmark; +12.01 pp AIPW on MBG).
R3 Ironic Typographic FYP Hijacking	X Quote Cascades & TikTok FYP	X quote-framing (11.47% of tweets; 18.53% of edges) boosts log views by +1.57 (AIPW z = 34.4); 47.97% of TikTok MBG comments induce 4-classifier pragmatic split	TikTok MBG Nested Thread ('*ibuk ngomongnya, TIMES NEW ROMAN, BOLD, CAPLOCK NYALA, 16, CTRL + E*')	Youth ridicule bureaucratic arrogance via UI/word-processor metaphors and quote-dunking—splitting literal NLP classifiers between neutral and negative while maximizing algorithmic engagement.
R4 Disconnective Transnational Exit	X Threads & Cross-Platform Tutorials	N = 4,768 unique #KaburAjaDulu posts: visa/scholarship tutorials average 151.8 likes & 22.1 retweets; 8.54% explicitly bridge #KaburAjaDulu with #IndonesiaGelap	#KaburAjaDulu Corpus ('*Angka tidak berbohong* #KaburAjaDulu... *Gaji di LN 20 juta... ikut meramaikan* #KaburAjaDulu #IndonesiaGelap')	Operationalizes disconnective action {o1}: youth convert domestic wage/tax disillusionment into collective exit logistics (Japan/Germany/WHV) rather than street confrontation.
R5 Affective Buzzer Counter Polarization	TikTok Level≥1 Replies & X Silos	TikTok nested replies (18.19%, n = 10,432) raise consensus negativity from 60.79% to 65.34% (AIPW +3.53 pp, z = 6.74, p = 1.57×10^{-11})	#KaburAjaDulu Patriotic Counter-Shaming (172.3 mean likes) & TikTok Level-1 Sub-Threads	Nested sub-threads and counter-framing trap users in dyadic moral shaming ('unpatriotic traitors' vs. 'regime buzzers'), generating high local excitation but low inter-community bridging (*Demo* & DPR cross-ratio = 6.4%).

Notes: Coded via abductive digital-ethnographic discourse analysis in strict compliance with Association of Internet Researchers (AoIR) Ethics Guidelines 3.0; all personal account handles in protest datasets are irreversibly SHA-hashed or de-identified.

3.4. Tier 4: fsQCA across 24 mobilization regimes

Table 6 and Figures 5–6 present our exact Ragin four-value fsQCA across all N = 24 empirically calibrated mobilization regimes. The set-theoretic necessity diagnostics (Table 6, Panel A) show a socio-technical asymmetry. ALGO_TACTICS comes closest to necessity for CROSS_CUTTING_REACH (consistency = 0.8586; all five conditions exceed 0.80 but none reaches the conventional 0.90), yet it also reaches 0.8094 necessity consistency for the negated outcome (~CROSS_CUTTING_REACH, Affective Echo-Chamber Encapsulation; RoN = 0.380). Algorithmic visibility tactics are thus common to both high-reach and low-reach regimes. Alone, they do not prevent siloed encapsulation. POROUS_DELIB is different. It has the highest necessity coverage (0.8010, RoN = 0.8417) for CROSS_CUTTING_REACH. Echo-chamber encapsulation is anchored by ~POROUS_DELIB (consistency = 0.8118, coverage = 0.8112) and ~CONNECTIVE_VOICE (coverage = 0.8185).

Table 6. Exact Ragin Four-Value Fuzzy-Set Qualitative Comparative Analysis (fsQCA) Across N = 24 Cross-Platform Mobilization Regimes: Necessity Diagnostics and Quine–McCluskey Sufficiency Pathways (Tier 4).

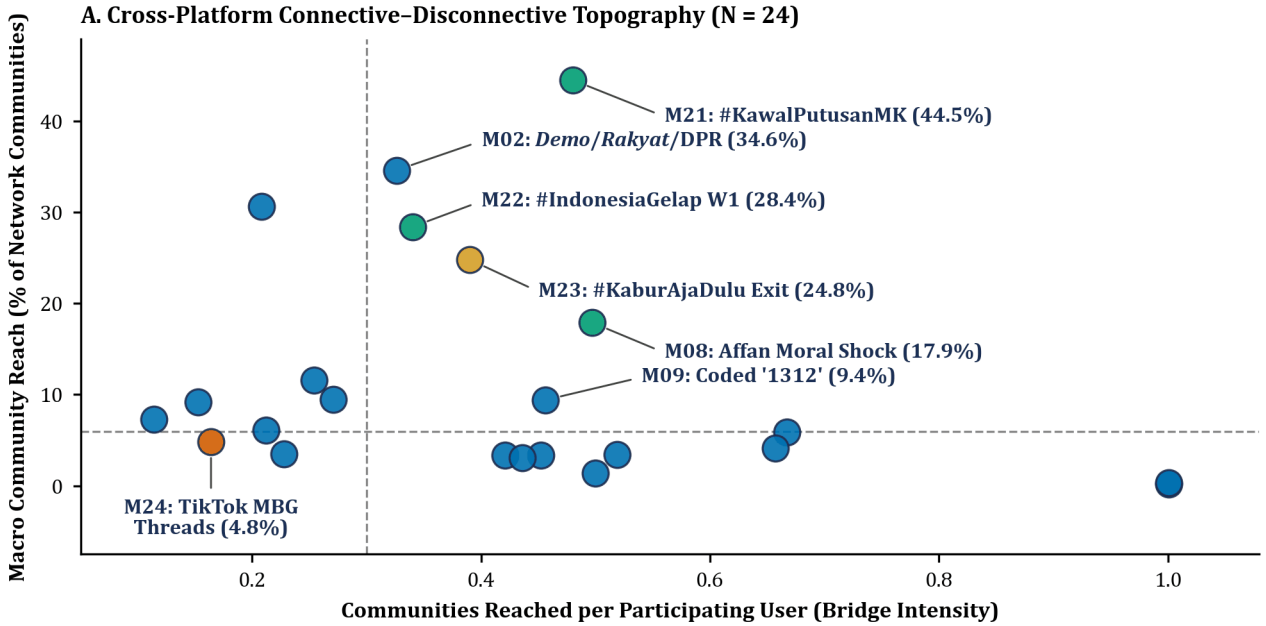
Condition / Conjunctural Pathway	Boolean Expression (5 Socio-Technical Conditions)	Consist. (Incl.)	PRI / RoN	Raw / Unique Cov.	Covered Empirical Regimes & Configurational Interpretation
Panel A: Set-Theoretic Necessity Analysis for Cross-Cutting Reach vs. Affective Echo Encapsulation (~Outcome)					
ALGO_TACTICS (Visibility & Algospeak Repertoire)	Necessity for CROSS_CUTTING_REACH / ~Outcome	0.8586 / 0.8094	RoN: 0.381 / 0.380	Cov: 0.536 / 0.534	Common to high- and low-reach regimes; insufficient alone.
CONNECTIVE_VOICE & MORAL_GRIEVANCE	Necessity for CROSS_CUTTING_REACH	0.8286 / 0.8003	RoN: 0.769 / 0.636	Cov: 0.745 / 0.636	Collective claim-making & inclusive moral shocks anchor broad reach
BRIDGE_BROKER & POROUS_DELIB	Necessity for CROSS_CUTTING_REACH	0.8003 / 0.8003	RoN: 0.612 / 0.842	Cov: 0.621 / 0.801	POROUS_DELIB yields highest single-condition coverage (0.801)
~POROUS_DELIB & ~CONNECTIVE_VOICE	Necessity for ~CROSS_CUTTING_REACH	0.8118 / 0.7315	RoN: 0.834 / 0.867	Cov: 0.811 / 0.819	Siloed sub-thread encapsulation drives echo-chamber fragmentation
Panel B: Sufficiency Solution for CROSS_CUTTING_REACH (Consistency = 0.8277, PRI = 0.7804, Coverage = 0.5433)					
Pathway B-P1 (Full Conjunctural Bridging Mobilization)	ALGO_TACTICS * BRIDGE_BROKER * MORAL_GRIEVANCE * CONNECTIVE_VOICE * POROUS_DELIB	0.8277	PRI = 0.7804	0.5433 / 0.5433	7 Core Waves: M02 (*Demo*/*Rakyat*), M03 (DPR), M05, M07, M08 (Affan), M21 (#KawalPutusanMK), M22 (#IndonesiaGelap)
Disconnective Mutual-Aid Outlier (Case M23)	ALGO_TACTICS * BRIDGE_BROKER * MORAL_GRIEVANCE * ~CONNECTIVE_VOICE * POROUS_DELIB	Outlier Y = 1.00	24.8% Reach	N = 4,768 Posts	M23 (#KaburAjaDulu Exit Wave): achieves broad reach via skill-exit mutual aid without street rallies

Condition / Conjunctural Pathway	Boolean Expression (5 Socio-Technical Conditions)	Consist. (Incl.)	PRI / RoN	Raw / Unique Cov.	Covered Empirical Regimes & Configurational Interpretation
Panel C: Asymmetric Sufficiency Solution for Echo-Chamber Encapsulation (~CROSS_CUTTING_REACH: Cons = 0.8753, PRI = 0.8507, Cov = 0.5693)					
Pathway ~B-P1 (Sectarian Invective Without Moral Framing)	BRIDGE_BROKER * ~MORAL_GRIEVANCE * ~CONNECTIVE_VOICE * ~POROUS_DELIB	0.9173	PRI = 0.9009	0.2968 / 0.0000	M12, M13, M16 (fragmented micro-clusters lacking universal moral frame)
Pathway ~B-P2 (Algorithmic Tactics in Siloed Reply Threads)	ALGO_TACTICS * MORAL_GRIEVANCE * ~CONNECTIVE_VOICE * ~POROUS_DELIB	0.8759	PRI = 0.8584	0.3779 / 0.1638	M24 (TikTok MBG Nested Reply Contention), M15, M17, M19 (highest unique cov.)
Pathway ~B-P3 (Low-Visibility Micro-Enclaves)	~ALGO_TACTICS * ~MORAL_GRIEVANCE * ~CONNECTIVE_VOICE * ~POROUS_DELIB	0.8584	PRI = 0.8350	0.1622 / 0.0276	M12, M20 (isolated low-tactic peripheral threads)
Pathway ~B-P4 (Hostile Coded Sloganeering Without Moral Frame)	ALGO_TACTICS * BRIDGE_BROKER * ~MORAL_GRIEVANCE * ~CONNECTIVE_VOICE	0.8562	PRI = 0.8174	0.3236 / 0.0543	M01, M13, M14 ('*anjing*/1312' vitriol), M16 (high heat, narrow reach)

Notes: Exact Ragin four-value fuzzy-set calibration (0.00, 0.33, 0.67, 1.00) across N = 24 empirically observed mobilization regimes (20 BERTopic X protest clusters M01–M20 plus 4 cross-platform waves M21–M24). Conservative Quine–McCluskey minimization with zero logical remainders (consistency >= 0.80, PRI >= 0.65). All five conditions exceed 0.80 but none reaches the conventional 0.90 necessity threshold. BRIDGE_BROKER, POROUS_DELIB, and the outcome derive from cross-community edges.

Conservative Quine–McCluskey minimization for CROSS_CUTTING_REACH (Table 6, Panel B; Figure 6A) identifies a single sufficient configuration, Pathway B-P1: ALGO_TACTICS * BRIDGE_BROKER * MORAL_GRIEVANCE * CONNECTIVE_VOICE * POROUS_DELIB (Solution Consistency = 0.8277, PRI = 0.7804, Coverage = 0.5433). It covers seven flagship mobilization streams: M21 (Aug 2024 #KawalPutusanMK / *Garuda Biru*, full 1.00 membership), M22 (Feb 2025 #IndonesiaGelap Wave 1), M08 (Affan Kurniawan moral-shock solidarity), M02 (*Demo*/*Rakyat*/DPR), M03, M05, and M07. Figure 6A also singles out Case M23 (#KaburAjaDulu Exit Wave) at (X = 0.00, Y = 1.00). M23 explicitly avoids collective street protest (~CONNECTIVE_VOICE = 1.00), so it falls outside B-P1. Even so, it achieves 24.8% cross-cutting reach through practical transnational mutual-aid brokerage. Minimizing ~CROSS_CUTTING_REACH (Table 6, Panel C; Solution Consistency = 0.8753, PRI = 0.8507, Coverage = 0.5693) reveals four asymmetric encapsulation pathways. Pathway ~B-P2 leads them (ALGO_TACTICS * MORAL_GRIEVANCE * ~CONNECTIVE_VOICE * ~POROUS_DELIB, consistency = 0.8759, unique coverage = 0.1638), exemplified by M24 TikTok MBG Nested Reply Contention. Pathways ~B-P1/~B-P4 (consistency = 0.9173 and 0.8562) cover hostile '1312/*anjing*' invective clusters M13, M14, and M16, which lack inclusive moral framing. Three regimes with high reach fall outside B-P1: M01 (outcome 1.00), M23 (1.00), and M09 (0.67), so B-P1 is sufficient but not necessary for reach, and its coverage is 0.5433. Without M21 the solution consistency is 0.8018, and without M01 it is 0.8199 (recomputed from the Figure 5B matrix).

Placing our four cross-platform macro waves (M21–M24) inside the calibrated matrix (Figure 5B) illustrates the theoretical argument. Constitutional urgency (#KawalPutusanMK, M21) and student budget resistance (#IndonesiaGelap, M22) each unite coded visual/hashtag tactics with grassroots bridge brokers and porous cross-cluster dialogue, and in those waves contention scales across 28.4% to 44.5% of network communities. Then the same policy frustration moves into #KaburAjaDulu (M23). Here youth substitute transnational exit mentorship (~CONNECTIVE_VOICE) while keeping porous peer brokerage (24.8% reach). M24 differs sharply. Fiscal-welfare grievances unfold inside TikTok's nested sub-thread architecture without cross-cluster brokers. Visibility tactics alone coincide with encapsulated, negative threads (4.8% reach; 65.34% nested negativity).



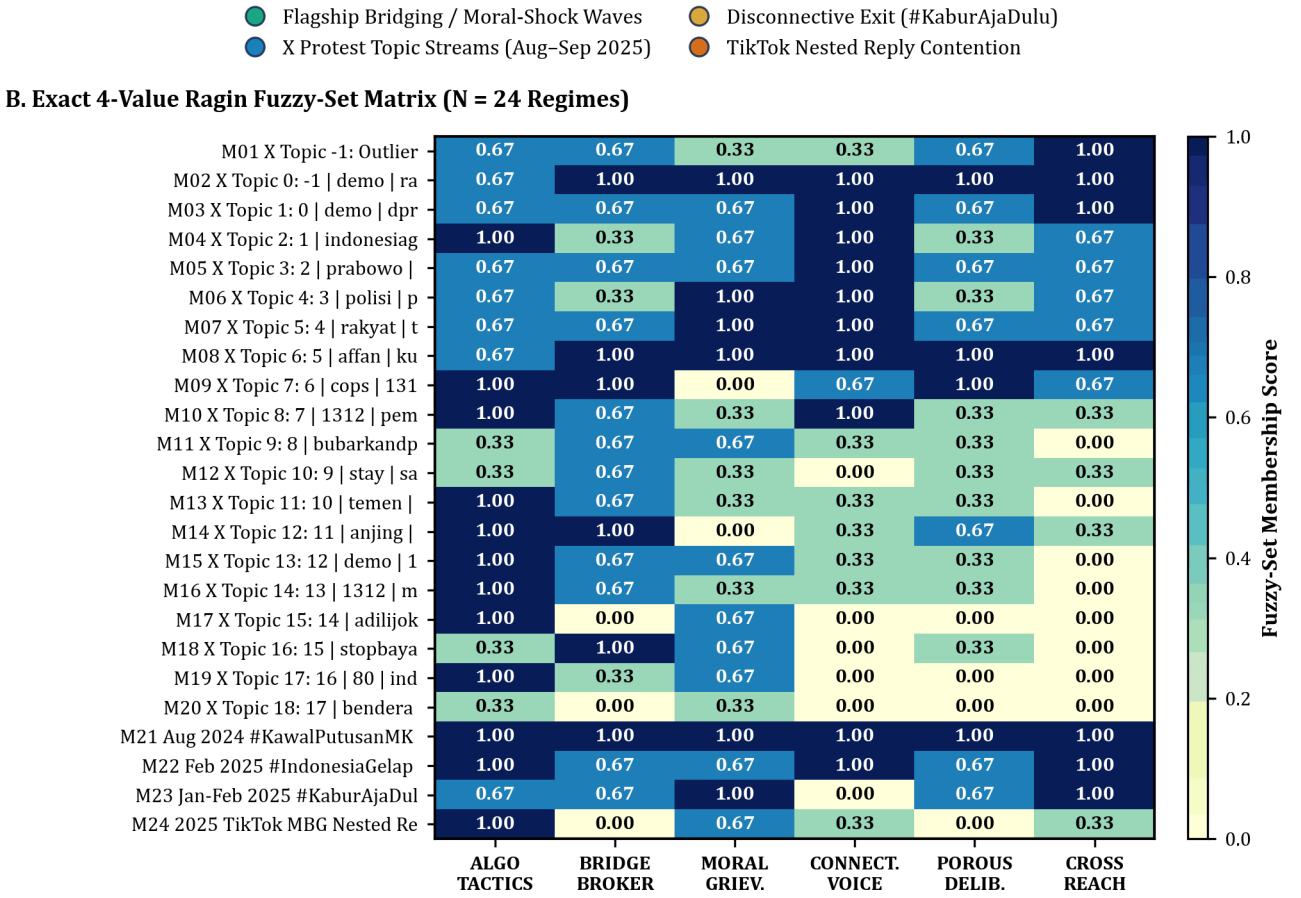
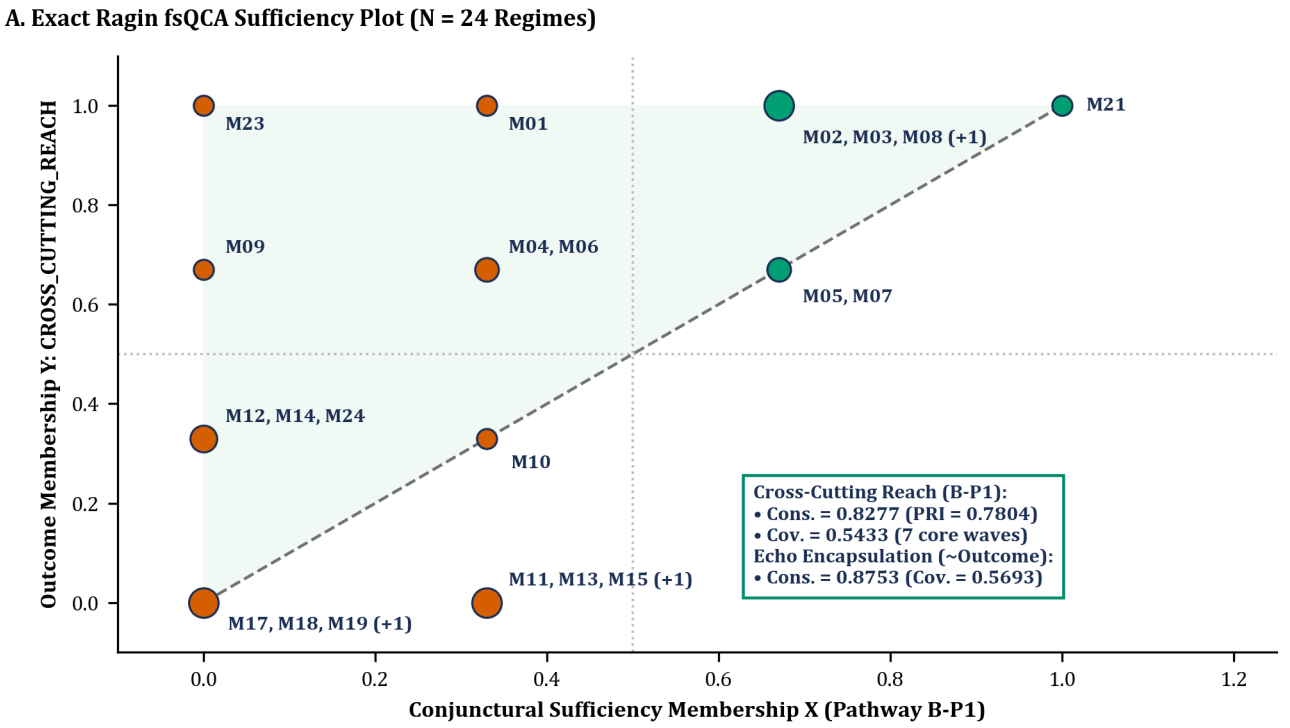


Figure 5. Cross-Platform Mobilization Topography and Four-Value Set-Theoretic Calibration Matrix Across 24 Regimes (Tier 4). Panel A maps all 24 empirical mobilization regimes across user bridge intensity (communities reached per user) and macro community reach (%), color-coded by platform and action mode. Panel B displays the complete 24 × 6 Ragin four-value fuzzy-set calibration matrix (ALGO_TACTICS, BRIDGE_BROKER, MORAL_GRIEVANCE, CONNECTIVE_VOICE, POROUS_DELIB, and CROSS_CUTTING_REACH).



B. Five-Pillar Socio-Technical & Youth Civic Resilience Framework

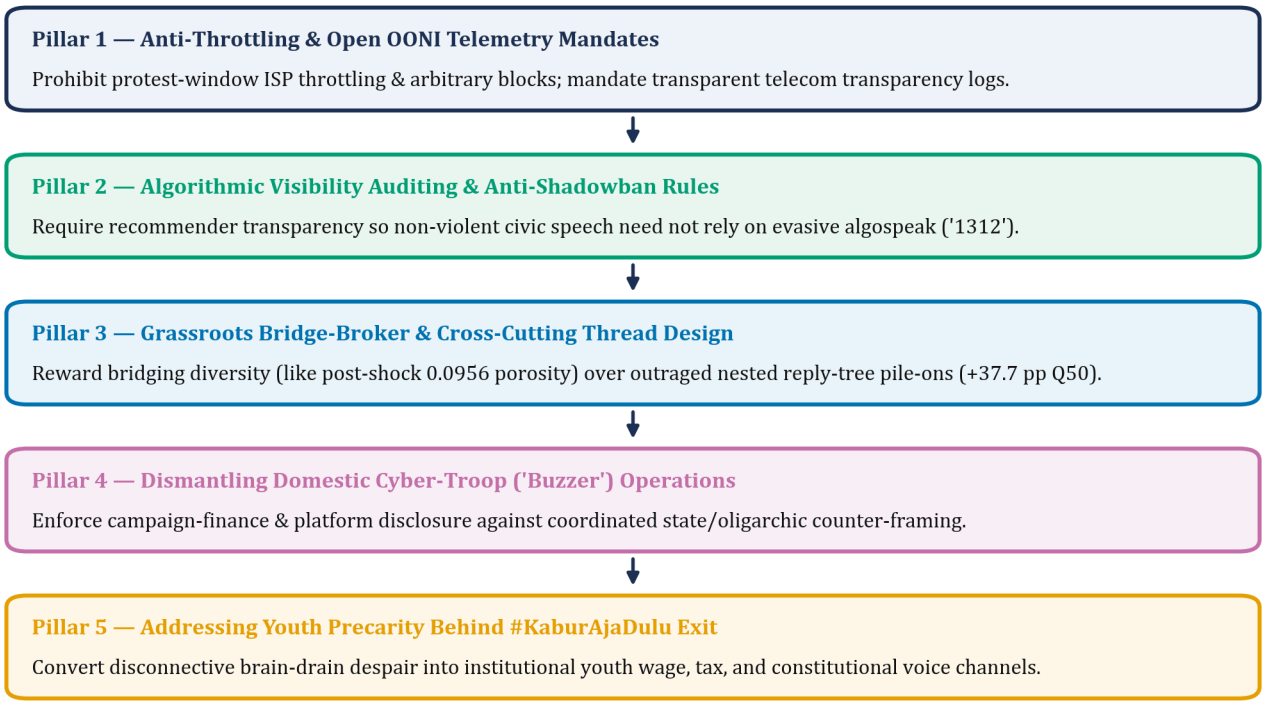


Figure 6. Set-Theoretic Sufficiency Verification and Socio-Technical Governance Framework for Hybrid Public Spheres. Panel A plots exact Ragin fsQCA outcome membership (CROSS_CUTTING_REACH) against conjunctural sufficiency membership (Pathway B-P1: Consistency = 0.8277, PRI = 0.7804, Coverage = 0.5433; Echo Encapsulation ~Outcome Consistency = 0.8753, Coverage = 0.5693) across all 24 regimes, highlighting M21 (#KawalPutusanMK) at (1.00, 1.00) and disconnective outlier M23 (#KaburAjaDulu) at (0.00, 1.00). Panel B synthesizes the five-pillar socio-technical and youth civic resilience framework.

3.5. Mixed-methods joint display and governance synthesis

Table 7 and Figure 6B bring our four empirical tiers together in a Mixed-Methods Joint Display.[64] Five sets of evidence sit side by side: OONI packet-level telemetry, X topological and RIF/AIPW estimates, TikTok nested polarization trajectories, digital-ethnographic repertoires (R1–R5), and set-theoretic pathways. The pairings yield five explicit Meta-Inferences. They also yield institutional governance pillars.

Our Joint Display yields five cross-method meta-inferences. We propose that neither computational network metrics nor qualitative discourse reading alone would have uncovered them.[62,64,72,73] First, Infrastructure Confirmation relates packet-level OONI probe volume (+0.268 log, p = 0.0317) to a possible pre-emptive platform diversification by activists across Waves 1–3, which the data do not measure. Second, Paradox Resolution accounts for a double effect of coded algospeak. It helps content survive censorship (R2/R3). It also amplifies Q90 extreme thread hostility (+60.86 pp). Third comes Discordance Diagnosis. TikTok and X's '*Demo* & DPR' cluster both show high comment volume but low inter-community bridging, and nested reply trees (+37.70 pp Q50 negativity) reward dyadic outrage over cross-cutting brokerage. Fourth, Contextual Expansion links spikes of patriotic shaming in #KaburAjaDulu (172.3 likes) to documented Indonesian cyber-troop ('buzzer') counter-operations.[45–47] Fifth, Theoretical Synthesis treats #IndonesiaGelap voice and #KaburAjaDulu exit as two expressions of one blocked youth socioeconomic and constitutional agency.

Table 7. Critical Mixed-Methods Integrative Joint Display: Triangulating Network Telemetry, Cross-Platform Econometrics, Ethnographic Repertoires, fsQCA, and the Five-Pillar Governance Architecture.

Hybrid Ecosystem Layer & Policy Pillar	Quantitative Telemetry / Network / AIPW-RIF Finding	Ethnographic Repertoire & Set-Theoretic Configuration	Mixed-Methods Meta-Inference & Socio-Technical Reform
1. Network-Layer Anti-Throttling & OONI Transparency (Pillar 1)	Indonesia OONI (10.07M probes): +0.268 log pooled probe volume in protest windows (p = 0.0317; driven by Wave 3 at 35.7k/day, while Wave 2 was below baseline); Bangladesh July 2024 blackout jumps 3.63%→12.99%.	Youth may shift to encrypted IM & circumvention tools when live-streaming slows (IM anomaly rates 2.11% → 2.71% across Waves 1–3; not statistically significant).	[Confirmation & Infrastructure Expansion]: Hybrid contention begins at the ISP packet layer. Prohibit unannounced protest-window throttling and mandate public telecom interference logs.
2. Algorithmic Visibility Auditing & Anti-Shadowban Rules (Pillar 2)	X quote-framing boosts log views by +1.572 (AIPW z = 34.37, E = 2.70); TikTok tactics split 4 NLP models on 47.97% of comments and the Q90 slope for visibility tactics is +60.86 pp.	Repertoires R2 & R3: youth deploy '1312', vowel-dropped strike calls ('sbaiknya kt mogok...'), & UI formatting satire ('TIMES NEW ROMAN...') to evade demotion.	[Paradox Resolution]: Opaque keyword moderation may push non-violent youth into evasive algospeak, which is associated with the largest Q90 negativity slope. Mandate algorithmic visibility audits for civic speech.
3. Grassroots Bridge Brokerage & Cross-Cutting Thread Design (Pillar 3)	99.21% of X Diffusion Drivers are grassroots citizens (+1.032 log views AIPW, z = 13.86; RIF peak +0.450 at Q75); Affan moral shock raises porosity +85.3% (p = 0.0029).	Repertoire R1 + fsQCA B-P1 (Cons = 0.8277) vs. ~B-P2 (TikTok nested threads = 0.8759, where level≥1 reply share has a slope of +37.70 pp at Q50).	[Discordance Diagnosis]: Outrage-ranked nested sub-threads may maximize dyadic hostility rather than bridging. Re-engineer feeds to reward cross-cluster bridging diversity over angry sub-replies.

Hybrid Ecosystem Layer & Policy Pillar	Quantitative Telemetry / Network / AIPW-RIF Finding	Ethnographic Repertoire & Set-Theoretic Configuration	Mixed-Methods Meta-Inference & Socio-Technical Reform
4. Dismantling Domestic Cyber-Troop ('Buzzer') Operations (Pillar 4)	Patriotic counter-shaming in #KaburAjaDulu triggers highest conflict engagement (172.3 mean likes, 27.2 RTs); *Demo* & DPR has 93.6% intra-silo confinement.	Repertoire R5 + fsQCA ~B-P1/~B-P4 (Cons = 0.856–0.917): ad-hominem 'traitor vs. buzzer' vitriol destroys moral-grievance bridging.	[Contextual Expansion]: Polarization may be amplified by coordinated influence operations {o34,o35,o36}. Enforce statutory disclosure and campaign-finance audits on paid cyber-troops.
5. Addressing Youth Precarity Behind #KaburAjaDulu Exit (Pillar 5)	#KaburAjaDulu (N = 4,768): visa/scholarship exit tutorials earn 151.8 likes (6.2× complaint posts) with 8.54% direct #IndonesiaGelap crossover.	Repertoire R4 + Case M23 (Disconnective Mutual-Aid Outlier: 24.8% reach under ~CONNECTIVE_VOICE): collective brain-drain logistics.	[Theoretical Synthesis]: Disconnective exit may be an alarm bell of blocked institutional voice. Pair digital rights with youth employment, fair taxation, and meritocratic governance.

Notes: Structured with reference to the Mixed Methods Appraisal Tool (MMAT)[74] and the joint-display approach illustrated in,[64] synthesizing 190,646 verified records across Tiers 1–4.

4. Discussion

4.1. The connective–disconnective continuum: voice, algospeak, and performative exit

Our multi-tier investigation advances digital-activism and political-communication scholarship in three ways. The first concerns theory. We juxtapose Indonesia's 2024–2025 connective protest waves (#KawalPutusanMK and #IndonesiaGelap) with #KaburAjaDulu (N = 4,768). Doing so extends recent theories of disconnective action[2,3,5,75] into a unified 'Connective–Disconnective Continuum.' European and North American accounts conceptualize disconnective action mainly through protest against a corporate sponsor[2,75] or safety-driven migration into private chat groups.[3] Global South youth face a different set of pressures at once: democratic backsliding, ageist formal labor bottlenecks, regressive consumption taxes, and cyber-troop manipulation and harassment.[18,45,76–78] Under these conditions, #KaburAjaDulu turns Albert Hirschman's private 'exit'[79] into a publicly networked, performative disconnection. Young citizens crowdsource Japanese, German, and Australian visa/scholarship blueprints, which earn 6.2× higher likes than pure grievance posts, and 8.54% explicitly link #KaburAjaDulu with #IndonesiaGelap. Disconnective exit therefore serves two roles. It resembles the practical, algorithmic mutual aid described on TikTok.[35] It is also a collective symbolic vote of no confidence, and that vote is met with intense nationalist counter-shaming (172.3 mean likes).

The continuum perspective also helps explain cycles of youth contention. Cases from contemporary Asia and the Global South range from the Milk Tea Alliance of Hong Kong, Thailand, and Myanmar[12–14,80,81] to Kenya's #RejectFinanceBill and Bangladesh's July 2024 Monsoon Uprising. In our reading, each shows shifts between quiet digital mutual aid, viral memetic exit, and sudden mass street assembly.[6,9,82] Institutions sometimes dismiss peaceful constitutional petitions (#KawalPutusanMK) or student budget critiques (#IndonesiaGelap). Disconnective repertoires (#KaburAjaDulu) may then preserve horizontal peer trust, data-sharing literacy, and shared moral framing while the streets are demobilized, in the way low-visibility networks sustain a movement between peaks.[15,75,82] Disconnective mutual-aid networks need not signal generational depoliticization. They may keep civic infrastructure alive. Then an acute moral shock ruptures public tolerance. Lethal state violence against an ordinary gig-economy worker is one example. At that point the latent infrastructure can re-synchronize quickly into connective street solidarity.

4.2. Platform affordances, grassroots brokerage, and the algospeak visibility paradox

Second, network-forensic X cascade analysis (Tier 2) and TikTok nested comment trees (Tier 3) together show how platform architectures shape civic solidarity versus affective hostility.[22,31,36,69,83] Consider X first. Rectifying the upstream '@' handle-linkage bug across 11,426 protest nodes shows that connective diffusion relies overwhelmingly on non-elite grassroots citizens (99.21% of Diffusion Drivers). Their cross-community bridge brokerage is associated with visibility that is higher by +1.032 log views after adjustment (AIPW $p < 1 \times 10^{-43}$). The association is largest across the middle-to-upper grassroots distribution (Q50–Q75). At Q90 the log in-degree slope is far larger (+2.446), which is consistent with legacy media and elite Attention Sinks holding the hub ceiling, although an elite indicator was not modeled. Abstract partisan outrage ('*Demo* & DPR') behaves differently. Of its interactions, 93.6% fall within Louvain communities. An inclusive human moral shock may puncture such silos. The death of gig-driver Affan Kurniawan coincided with 7-hop cascades and with a +85.3% rise in network-wide porosity (p = 0.0029).

TikTok differs. Its FYP interest clustering[22] and nested level >= 1 reply sub-threads lack cross-cluster quote-bridging affordances. Sub-thread replies are accompanied by consensus negativity that is higher by +3.53 pp overall ($p = 1.57 \times 10^{-11}$), and the slope for nested reply share is +37.70 pp at the thread median Q50 ($p = 1.46 \times 10^{-05}$). Our ethnographic and RIF results suggest what we call an 'Algospeak Visibility Paradox'.[29,30] Ironic UI formatting satire ('*TIMES NEW ROMAN, BOLD, CAPLOCK NYALA*') may evade literal NLP classifiers, which is consistent with the 47.97% four-model disagreement in the corpus as a whole. Overt slogans do the opposite. Typographic and coded ones ('1312', ALL-CAPS accusations) show the largest Q90 slope (+60.86 pp, p = 0.0235, uncorrected), and they appear in low-reach configurations (fsQCA ~B-P2 = 0.8759; ~B-P4 = 0.8562).

Methodologically, this 47.97% four-classifier pragmatic split on TikTok carries a clear lesson for computational communication researchers.[40,49,84,85] Off-the-shelf sentiment or toxicity models are trained on literal formal prose. They may misclassify youth ironic mimicry, UI metaphors, and orthographic algospeak. Pairing multi-classifier divergence metrics with human-linguist benchmarks (N = 9,882) and abductive digital ethnography keeps researchers from mistaking playful anti-authoritarian satire for neutral apathy, and the same pairing separates inclusive moral-shock solidarity (M08 Affan Kurniawan; M21 #KawalPutusanMK) from insular sectarian vitriol (M13, M14, M16). Set-theoretically, our 24-regime fsQCA points one way. Algorithmic tactics (ALGO_TACTICS) are common in high-reach regimes (consistency 0.8586). The best-fitting

sufficient configuration for broad reach pairs visibility tactics with grassroots bridge brokers (BRIDGE_BROKER), universal moral grievances (MORAL_GRIEVANCE), and porous cross-cutting deliberation (POROUS_DELIB).

4.3. Governance implications, scope conditions, and future research

Third, OONI packet-level telemetry (Tier 1) and set-theoretic fsQCA (Tier 4) together point to governance reforms across five socio-technical layers (Table 7; Figure 6B). Five measures follow. (1) Prohibit protest-window bandwidth throttling. Mandate open telecom interference logs.[86] (2) Institute independent algorithmic visibility audits, so that lawful youth dissent need not rely on polarizing algospeak.[29,87] (3) Redesign platform comment rankings to up-weight cross-cluster bridging diversity over angry nested reply pile-ons.[36,69,83] (4) Enforce campaign-finance and platform transparency rules in order to dismantle paid domestic cyber-troop ('buzzer') operations.[45–47] (5) Address the youth wage, tax, and institutional-trust deficits. These fuel #KaburAjaDulu.

Each pillar targets a bottleneck that our multi-tier evidence points to. Under Pillars 1 and 2, statutory digital-governance frameworks in emerging democracies should move away from elastic 'public-order' takedown powers, such as overly broad defamation and public-disturbance clauses under Indonesia's Electronic Information and Transactions Law (UU ITE), and toward mandatory ISP traffic-management disclosure and auditable recommender transparency logs. Consider what changes if young citizens and journalists can verify in real time that live parliamentary broadcasts, constitutional petitions (#KawalPutusanMK), and police-accountability videos are neither bandwidth-throttled nor algorithmically shadowbanned. The structural incentive to cloak civic speech in coded language may then diminish. Under Pillar 3, platform engineering teams at TikTok, X, and Meta could test whether nested sub-thread negativity (a +37.70 pp slope at median Q50) falls under a different ranking. One option is to replace raw reply-velocity sorting with bridging-consensus ranking algorithms, which resemble Community Notes matrix-factorization scoring. Such algorithms would surface comments endorsed across otherwise disconnected Louvain clusters instead of rewarding dyadic outrage. The data do not test such an intervention.

Pillars 4 and 5 rest on a different recognition. Affective polarization and youth disconnection are ultimately rooted in political-economic accountability, not in technology alone. Indonesia's anti-corruption and electoral cycles document this pattern.[45–47] Paid cyber-troop networks have used nationalist shaming against student critics, and similar counter-shaming appears in the #KaburAjaDulu corpus, although we did not test who produced it. Such campaigns can turn legitimate policy deliberation over fiscal priorities, parliamentary allowances, and MBG program implementation into zero-sum identity conflict. Statutory campaign-finance audits, procurement disclosure for state digital-relations contractors, and coordinated inauthentic behavior takedowns may help restore deliberative trust. Turning the brain-drain disillusionment of #KaburAjaDulu back into constructive democratic voice calls for three further steps. Ageist formal recruitment barriers should be removed. Gig-economy couriers and young precarious workers need protection, since their vulnerability made Affan Kurniawan's death a nationwide moral watershed. Youth Participatory Budgeting councils with binding oversight could be considered.

Several methodological scope conditions deserve transparent acknowledgment. They also point to fertile directions for future comparative research. First, OONI provides one of the largest open records of network interference globally (10.07 million Indonesian probes across 1,002 days). Yet probe execution is citizen-initiated. That fact may explain why measurement volume rose in some mobilization windows (+0.268 log pooled) alongside shifting domain mixes. Future research should pair OONI active probing with passive Border Gateway Protocol (BGP) and Internet Outage Detection and Analysis (IODA) telemetry, so that subnational cellular throttling around protest squares can be localized. Second, X and TikTok accounts cannot be linked. At the individual-user level, deterministic linkage would violate AoIR 3.0 de-identification ethics.[54] Our cross-platform integration therefore works at the discourse-repertoire and mobilization-regime levels (N = 24). Combining computational network forensics with longitudinal, opt-in youth media diaries across Indonesia, Thailand, Kenya, and Bangladesh will shed further light on how individual young citizens sequence voice, algospeak, and exit over the life course. Such work is the next step. Further limits apply. The sentiment classifiers were not validated for irony, the community partitions depend on the Louvain resolution, the fsQCA rests on 24 author-coded regimes with overlapping data, the archives were not collected for these questions, and none of the estimates identifies a causal effect.

5. Conclusion

This study synthesizes 190,646 public records: OONI network telemetry, multi-wave X protest graphs, #KaburAjaDulu disconnective exit threads, and nested TikTok policy contention. The results fit contemporary youth activism operating across a connective–disconnective continuum. Network friction, algorithmic visibility, and community brokerage appear to shape it. In Indonesia, citizen censorship-monitoring probes were higher in protest windows (+0.268 log pooled, $p = 0.0317$), a rise driven by Wave 3 (35,701.8 daily probes). Ordinary grassroots citizens make up 99.21% of cross-community X protest Diffusion Drivers (+1.032 log views AIPW, $p < 1 \times 10^{-43}$). Quote-framing goes with higher reach (+1.572 log views, $z = 34.37$). Louvain cross-community porosity was +85.3% higher after the moral shock around gig-worker Affan Kurniawan's death ($p = 0.0029$). Contention also bifurcates. It splits in two where youth confront unresponsive institutions or outrage-ranked nested comment trees. One branch is #KaburAjaDulu transnational exit mutual aid (151.8 mean likes; 8.54% #IndonesiaGelap crossover). The other is polarized TikTok sub-thread pile-ons (slopes of +37.70 pp at median Q50 for nested replies and +60.86 pp at Q90 for visibility tactics). Exact four-value fsQCA across 24 regimes indicates that algorithmic visibility tactics are linked to broad cross-cutting reach (Consistency = 0.8277) in regimes that also have grassroots bridge brokers, inclusive moral grievances, connective voice, and porous deliberation. Configurations that lack these features are linked to echo-chamber encapsulation (Consistency = 0.8753).

6. Declarations

Statement on the Use of Artificial Intelligence

None. The authors declare that no generative artificial intelligence tools were used in the design, analysis, or writing of this manuscript.

Author Contribution Statement

Conceptualization: A.F.A. Methodology: A.F.A. Software: A.F.A. Validation: S.V., S.D. Formal analysis: A.F.A. Investigation: A.F.A., S.V. Resources: A.F.A. Data curation: A.F.A. Writing – original draft: A.F.A. Writing – review & editing: S.V., S.D. Visualization: A.F.A. Supervision: S.D. Project administration: A.F.A.

Funding Statement

This research received no external grant funding from public, commercial, or not-for-profit agencies.

Conflict of Interest / Competing Interests

The authors declare no financial, commercial, partisan, or institutional competing interests.

Data Availability Statement

All 190,646 public records (51.01 MB across 9 archives), the SHA-256 verification manifest, the harmonized tier 1 to tier 4 CSV matrices, the Python scripts for the OONI event-window analysis, the stripped-'@' network linkage, the doubly robust AIPW, the Firpo–Fortin–Lemieux RIF quantile regressions and the Quine–McCluskey fsQCA, and the complete JSON analytical outputs are kept in the project replication package.

Ethics Approval and Consent to Participate

This study analyzes only publicly archived, de-identified open-science network telemetry and social-media benchmark repositories, in accordance with the Association of Internet Researchers (AoIR) Ethics Guidelines 3.0. All personal usernames in the August–September 2025 Indonesian protest network repository were irreversibly anonymized by one-way cryptographic hashing before release, and all illustrative digital-ethnographic excerpts omit personal identifiers; no human-subjects intervention or private-group infiltration took place.

Consent for Publication

Not applicable. No personally identifiable handles, private messages, or biometric media are reproduced.

Acknowledgments

The authors gratefully acknowledge the Open Observatory of Network Interference (OONI), Keinan Lidzikri Rahmandika, Dian Puteri Ramadhani, and Andry Alamsyah (CC BY 4.0 Indonesian protest network repository), and the open-science contributors of the #IndonesiaGelap, #KawalPutusanMK, #KaburAjaDulu, and Indonesian TikTok benchmark archives.

7. References

1. Bennett WL, Segerberg A. The logic of connective action: digital media and the personalization of contentious politics. Information, Communication & Society. 2012;15(5):739-768. doi:10.1080/1369118x.2012.670661
2. Just SN, Christensen JF, Schwarzkopf S. Disconnective action: Online activism against a corporate sponsorship at WorldPride 2021. New Media & Society. 2025;27(1):502-521. doi:10.1177/14614448231178775
3. Zhu Q. From connective to disconnective action: how safety shapes political participation repertoires in instant messaging groups. Information, Communication & Society. 2026;29(12):3653-3670. doi:10.1080/1369118x.2025.2609786
4. Martin ZC, Riedl MJ, Woolley SC. How pro- and anti-abortion activists use encrypted messaging apps in post- Roe America. Big Data & Society. 2023;10(2):20539517231221736. doi:10.1177/20539517231221736
5. Rahbari M, Safari H, Nanvayi A. Disconnective practices and partisan polarization: Persian Twitter's fragmented public sphere. New Media & Society. Published online 2026 Apr 29. doi:10.1177/14614448261433479
6. Baran Z, Stoltenberg D. Dynamics of scale shift: Contentious places and hybrid activism on social media. New Media & Society. 2025;27(9):5088-5109. doi:10.1177/14614448241247314
7. Chen W, Yao Z, Tan H. From clicktivism to outsourced activism: Spectacle, dual outsourcing, and the connective logic in platform philanthropy. New Media & Society. Published online 2026 Feb 2. doi:10.1177/14614448251413710
8. Halupka M. The legitimisation of clicktivism. Australian Journal of Political Science. 2018;53(1):130-141. doi:10.1080/10361146.2017.1416586
9. Eckardt J, Turgeon M, Abul-Fottouh D, et al. Episodes of sustained protest: temporal patterns of online mobilization on X. Information, Communication & Society. 2026;29(10):2845-2864. doi:10.1080/1369118x.2025.2585094
10. Larsson AO, Tønnesen H, Magin M, et al. Calls to (what kind of?) action: A framework for comparing political actors' campaign strategies across social media platforms. New Media & Society. 2025;27(7):3807-3828. doi:10.1177/14614448241229156
11. Obia V. Twitter activism: Understanding the Twittersphere as the foremost community for activism and dragging in Nigeria. New Media & Society. 2025;27(1):151-167. doi:10.1177/14614448231172967
12. Lukito J, Lee T, Martin Z, et al. Connective action in Myanmar: a mixed-method analysis of Spring Revolution. Information, Communication & Society. 2024;27(7):1422-1440. doi:10.1080/1369118x.2023.2289973
13. Chan DSW. Political Resistance in the Marketplace: Consumer Activism in the Milk Tea Alliance. Journal of Contemporary Asia. 2024;54(4):643-666. doi:10.1080/00472336.2023.2236414
14. Phattharathanasut T. Transnational Youth Activist Networks in Asia: The Evolution and Dynamics of the Milk Tea Alliance. Annali di Ca' Foscari. Serie orientale. Published online 2024 Dec 4. doi:10.30687/annor/2385-3042/2024/02/007
15. Marques de Mesquita C. Meeting the challenge of social mobilization with participant turnover: knowledge transmission in the U.S. youth climate movement. Social Movement Studies. Published online 2026 Oct 31. doi:10.1080/14742837.2026.2755055
16. Pfetsch B, Stoltenberg D, Baran Z, et al. Protest locations and digital affordances in environmental communication: patterns and issues of scaling in movement activism. Social Movement Studies. Published online 2026 Nov 3. doi:10.1080/14742837.2026.2755577
17. Betancor Nuez G. Territorial resistance and the spillover of protest. Lessons from the 20-A mobilization in the Canary Islands. Social Movement Studies. Published online 2025 Jun 3. doi:10.1080/14742837.2025.2512718
18. Yasmine DI, Colombijn F, Deursen AJAMV, et al. Internet skills, digital engagement, and outcomes among urban youth in Jakarta, Indonesia: incorporating a Global South context in measuring digital inequality. Information, Communication & Society. 2025;28(15):2774-2794. doi:10.1080/1369118x.2025.2479778
19. Hockin-Boyers H, Vertinsky P, Norman M, et al. Training the algorithm: Agency and algorithmic injustice in Instagram's 'whitewashed' health and fitness spaces. New Media & Society. 2026;28(9):4729-4751. doi:10.1177/14614448251366172
20. Karizat N, Delmonaco D, Eslami M, et al. Algorithmic Folk Theories and Identity: How TikTok Users Co-Produce Knowledge of Identity and Engage in Algorithmic Resistance. Proceedings of the ACM on Human-Computer Interaction. 2021;5(CSCW2):1-44. doi:10.1145/3476046
21. Delmonaco D, Mayworm S, Thach H, et al. "What are you doing, TikTok?" : How Marginalized Social Media Users Perceive, Theorize, and "Prove" Shadowbanning. Proceedings of the ACM on Human-Computer Interaction. 2024;8(CSCW1):1-39. doi:10.1145/3637431

22. Gerbaudo P. TikTok and the algorithmic transformation of social media publics: From social networks to social interest clusters. New Media & Society. 2026;28(3):1019-1036. doi:10.1177/14614448241304106
23. Tsinovoi A, Munk AK. Topologies of visibility: A space-sensitive approach to online visibility analysis. Big Data & Society. 2026;13(1):20539517261426451. doi:10.1177/20539517261426451
24. Beacken GD. Strategic visibility in precarious times: Ethnoreligious content creators and algorithmic navigation on Instagram. New Media & Society. Published online 2026 Apr 30. doi:10.1177/14614448261446580
25. Stegeman HM, Are C, Poell T. Strategic Invisibility: How Creators Manage the Risks and Constraints of Online Hyper(In)Visibility. Social Media + Society. 2024;10(2):20563051241244674. doi:10.1177/20563051241244674
26. Broqvist M. The platform other: Feminist activists' strategies in Instagram's visibility game. Platforms & Society. 2026;3:29768624261509697. doi:10.1177/29768624261509697
27. Liu AY. Ephemeral visibility and externally visible production: How algorithmic automation accelerates fans' data work. New Media & Society. 2026;28(10):5502-5524. doi:10.1177/14614448251393480
28. Qiu Z, Du J, Yu IY, et al. Algorithmic muteness: How algorithmic management obstructs platform content operators' resonance with their labor. New Media & Society. Published online 2026 Aug 4. doi:10.1177/14614448261472307
29. Steen E, Yurechko K, Klug D. You Can (Not) Say What You Want: Using Algospeak to Contest and Evade Algorithmic Content Moderation on TikTok. Social Media + Society. 2023;9(3):20563051231194586. doi:10.1177/20563051231194586
30. Elyamany N, Al Agroudi R, Hasib J, et al. Algospeak as algorithmic negotiation: multimodal strategies, platform governance, and the politics of visibility on TikTok. Language and Semiotic Studies. 2026. doi:10.1515/lass-2026-0031
31. Li M, Suk J, Zhang Y, Pevehouse JC, Sun Y, Kwon H, et al. Platform affordances, discursive opportunities, and social media activism: A cross-platform analysis of #MeToo on Twitter, Facebook, and Reddit, 2017–2020. New Media & Society. 2026;28(1):119-147. doi:10.1177/14614448241285562
32. Schoon A, Bosch T. TikTok and memetic activism against racism in South Africa. Information, Communication & Society. 2024;27(16):2760-2775. doi:10.1080/1369118x.2023.2295356
33. Zhao X, Abidin C. The "Fox Eye" Challenge Trend: Anti-Racism Work, Platform Affordances, and the Vernacular of Gesticular Activism on TikTok. Social Media + Society. 2023;9(1):20563051231157590. doi:10.1177/20563051231157590
34. Meyer H. Hearts for hating Activists: how far-right actors dominate polarized TikTok debates on climate protest. Information, Communication & Society. Published online 2026 Oct 11. doi:10.1080/1369118x.2026.2737399
35. Maris E, Caplan R, Thach H. Taking back and giving back on TikTok: Algorithmic mutual aid in the platform economy. New Media & Society. 2025;27(7):4071-4089. doi:10.1177/14614448241238396
36. Törnberg P. How digital media drive affective polarization through partisan sorting. Proceedings of the National Academy of Sciences. 2022;119(42):e2207159119. doi:10.1073/pnas.2207159119
37. Hutchens MJ, Hmielowski JD, Beam MA. Reinforcing spirals of political discussion and affective polarization. Communication Monographs. 2019;86(3):357-376. doi:10.1080/03637751.2019.1575255
38. Allcott H, Braghieri L, Eichmeyer S, et al. The Welfare Effects of Social Media. American Economic Review. 2020;110(3):629-676. doi:10.1257/aer.20190658
39. Chan M, Yi J. Social Media Use and Political Engagement in Polarized Times. Examining the Contextual Roles of Issue and Affective Polarization in Developed Democracies. Political Communication. 2024;41(5):743-762. doi:10.1080/10584609.2024.2325423
40. Schemer C, Langmann K, Hasell A, et al. Does the Method Affect the Outcome? How Measures of Partisan Slant of Media Outlets and Affective Polarization Drive Results About Polarization in the United States. Political Communication. Published online 2026 Jul 5. doi:10.1080/10584609.2026.2699105
41. Kubin E, von Sikorski C. The role of (social) media in political polarization: a systematic review. Annals of the International Communication Association. 2021;45(3):188-206. doi:10.1080/23808985.2021.1976070
42. Bossetta M, Schmøkel R. Cross-Platform Emotions and Audience Engagement in Social Media Political Campaigning: Comparing Candidates' Facebook and Instagram Images in the 2020 US Election. Political Communication. 2023;40(1):48-68. doi:10.1080/10584609.2022.2128949
43. Coe K, Kenski K, Rains SA. Online and Uncivil? Patterns and Determinants of Incivility in Newspaper Website Comments. Journal of Communication. 2014;64(4):658-679. doi:10.1111/jcom.12104
44. Arugute N, Calvo E, Ventura T. Network activated frames: content sharing and perceived polarization in social media. Journal of Communication. 2023;73(1):14-24. doi:10.1093/joc/jqac035
45. Wijayanto, Berenschot W, Sastramidjaja Y, et al. The Infrastructure of Domestic Influence Operations: Cyber Troops and Public Opinion Manipulation Through Social Media in Indonesia. The International Journal of Press/Politics. 2026;31(3):551-569. doi:10.1177/19401612241297832
46. Wijayanto W, Berenschot W, Suwana F. KPK and Taliban: Cyber Troops and the Social Media Influence Operation to Weaken Indonesia's Anti-corruption Body. Indonesia. 2025;119(1):103-121. doi:10.1353/ind.2025.a961929
47. Masduki. Cyber-troops, digital attacks, and media freedom in Indonesia. Asian Journal of Communication. 2022;32(3):218-233. doi:10.1080/01292986.2022.2062609
48. Grinko M, Qalandar S, Randall D, et al. Nationalizing the Internet to Break a Protest Movement: Internet Shutdown and Counter-Appropriation in Iran of Late 2019. Proceedings of the ACM on Human-Computer Interaction. 2022;6(CSCW2):1-21. doi:10.1145/3555205
49. Özkula SM, Reilly PJ, Hayes J. Easy data, same old platforms? A systematic review of digital activism methodologies. Information, Communication & Society. 2023;26(7):1470-1489. doi:10.1080/1369118x.2021.2013918
50. Tufekci Z. Big Questions for Social Media Big Data: Representativeness, Validity and Other Methodological Pitfalls. Proceedings of the International AAAI Conference on Web and Social Media. 2014;8(1):505-514. doi:10.1609/icwsm.v8i1.14517
51. Bode L, Vraga EK. Studying Politics Across Media. Political Communication. 2018;35(1):1-7. doi:10.1080/10584609.2017.1334730
52. Filastò A, Appelbaum J. OONI: Open Observatory of Network Interference. In: 2nd USENIX Workshop on Free and Open Communications on the Internet (FOCI 12). Bellevue, WA: USENIX Association; 2012. Available from: https://www.usenix.org/conference/foci12/workshop-program/presentation/Filastò
53. Irsyad MRN. *Dataset Komentar TikTok MBG (Makan Bergizi Gratis)* [TikTok comment dataset on the Free Nutritious Meals program] [dataset]. Kaggle. 2026. doi:10.34740/kaggle/dsv/16476771
54. franzke AS, Bechmann A, Zimmer M, Ess C; Association of Internet Researchers. Internet research: ethical guidelines 3.0. Chicago: Association of Internet Researchers; 2020. Available from: https://aoir.org/reports/ethics3.pdf
55. Blondel VD, Guillaume JL, Lambiotte R, et al. Fast unfolding of communities in large networks. Journal of Statistical Mechanics: Theory and Experiment. 2008;2008(10):P10008. doi:10.1088/1742-5468/2008/10/p10008
56. Firpo S, Fortin NM, Lemieux T. Unconditional Quantile Regressions. Econometrica. 2009;77(3):953-973. doi:10.3982/ecta6822
57. Rios-Avila F, Maroto ML. Moving Beyond Linear Regression: Implementing and Interpreting Quantile Regression Models With Fixed Effects. Sociological Methods & Research. 2024;53(2):639-682. doi:10.1177/00491241211036165
58. MacKinnon JG, White H. Some heteroskedasticity-consistent covariance matrix estimators with improved finite sample

properties. Journal of Econometrics. 1985;29(3):305-325. doi:10.1016/0304-4076(85)90158-7

59. Bang H, Robins JM. Doubly Robust Estimation in Missing Data and Causal Inference Models. Biometrics. 2005;61(4):962-973. doi:10.1111/j.1541-0420.2005.00377.x
60. VanderWeele TJ, Ding P. Sensitivity Analysis in Observational Research: Introducing the E-Value. Annals of Internal Medicine. 2017;167(4):268-274. doi:10.7326/m16-2607
61. Cinelli C, Hazlett C. Making Sense of Sensitivity: Extending Omitted Variable Bias. Journal of the Royal Statistical Society Series B: Statistical Methodology. 2020;82(1):39-67. doi:10.1111/rssb.12348
62. Behrens L, Rohlfing I. The Integration of Bayesian Regression Analysis and Bayesian Process Tracing in Mixed-Methods Research. Sociological Methods & Research. 2026;55(1):186-218. doi:10.1177/00491241241295336
63. Rohlfing I. An Exploration of the Presence of Positive-Results Bias in Qualitative Comparative Analysis. Sociological Methods & Research. 2026;55(3):957-980. doi:10.1177/00491241251357948
64. Chan GH, Lo TW. A Mixed Methods Analysis of Political Graffiti: Demonstrating Integration Through Joint Display Using Lennon Wall Hong Kong as an Example. Journal of Mixed Methods Research. 2026;20(1):84-100. doi:10.1177/15586898251362915
65. Ragin CC. Redesigning social inquiry: fuzzy sets and beyond. Chicago: University of Chicago Press; 2008. doi:10.7208/chicago/9780226702797.001.0001
66. Grootendorst M. BERTopic: neural topic modeling with a class-based TF-IDF procedure. arXiv. 2022. doi:10.48550/arXiv.2203.05794
67. Vargas-Leon P. Tracking Internet Shutdown Practices: Democracies and Hybrid Regimes. The Turn to Infrastructure in Internet Governance. Published online 2016. doi:10.1057/9781137483591_9
68. Silas J, Paskarina C, Herdiansyah AG. Which's more Powerful Digital Power in Papua: Internet Shutdown or Internet Throttling?. Journal of Governance. 2024;9(2). doi:10.31506/jog.v9i2.24197
69. Piccardi T, Saveski M, Jia C, et al. Reranking partisan animosity in algorithmic social media feeds alters affective polarization. Science. 2025;390(6776):eadu5584. doi:10.1126/science.adu5584
70. Lee A. Invisible networked publics and hidden contention: Youth activism and social media tactics under repression. New Media & Society. 2018;20(11):4095-4115. doi:10.1177/1461444818768063
71. Ahmed S, Masood M. Breaking Barriers With Memes: How Memes Bridge Political Cynicism to Online Political Participation. Social Media + Society. 2024;10(2):20563051241261277. doi:10.1177/20563051241261277
72. Fetters MD, Curry LA, Creswell JW. Achieving Integration in Mixed Methods Designs—Principles and Practices. Health Services Research. 2013;48(6pt2):2134-2156. doi:10.1111/1475-6773.12117
73. Johnson RE, Grove AL, Clarke A. Pillar Integration Process: A Joint Display Technique to Integrate Data in Mixed Methods Research. Journal of Mixed Methods Research. 2019;13(3):301-320. doi:10.1177/1558689817743108
74. Hong QN, Fàbregues S, Bartlett G, et al. The Mixed Methods Appraisal Tool (MMAT) version 2018 for information professionals and researchers. Education for Information. 2018;34(4):285-291. doi:10.3233/efi-180221
75. Kaun A, Treré E. Repression, resistance and lifestyle: charting (dis)connection and activism in times of accelerated capitalism. Social Movement Studies. 2020;19(5-6):697-715. doi:10.1080/14742837.2018.1555752
76. Power TP. Jokowi's Authoritarian Turn and Indonesia's Democratic Decline. Bulletin of Indonesian Economic Studies. 2018;54(3):307-338. doi:10.1080/00074918.2018.1549918
77. Warburton E, Aspinall E, Post-doctoral research fellow at the Asia Research Institute, National University of Singapore. Explaining Indonesia's Democratic Regression: Structure, Agency and Popular Opinion. Contemporary Southeast Asia. 2018;41(2):255-285. doi:10.1355/cs41-2k
78. Premandaru I, Adrison V. The Distributional Effects of VAT Rate Changes: Evidence from Indonesian Household Food Expenditure. Journal of Tax Reform. 2026;12(1):158-176. doi:10.15826/jtr.2026.12.1.245
79. Hirschman AO. Exit, voice, and loyalty: responses to decline in firms, organizations, and states. Cambridge, MA: Harvard University Press; 1970.
80. Hossain SMI. Digital repression and online resistance: new media in mobilizing the July 2024 uprising in Bangladesh. Electronic Journal of New Media. 2026;10(2):370-401. doi:10.17932/iau.ejnm.25480200.2026/ejnm_v10i2005
81. Ouma SO. Youth, Digital Communication and National Security in Kenya. National Security: A Journal of the National Defence University-Kenya. 2025;3(2):132-148. doi:10.64403/89txsx23
82. Taylor V, Crossley AD. Abeyance. The Wiley-Blackwell Encyclopedia of Social and Political Movements. Published online 2022 Sep 27. doi:10.1002/9780470674871.wbespm001.pub2
83. Bossetta M, Dutceac Segesten A, Bonacci D. Reconceptualizing Cross-Cutting Political Expression on Social Media: A Case Study of Facebook Comments During the 2016 Brexit Referendum. Political Communication. 2023;40(6):719-741. doi:10.1080/10584609.2023.2222370
84. van Atteveldt W, van der Velden MACG, Boukes M. The Validity of Sentiment Analysis: Comparing Manual Annotation, Crowd-Coding, Dictionary Approaches, and Machine Learning Algorithms. Communication Methods and Measures. 2021;15(2):121-140. doi:10.1080/19312458.2020.1869198
85. Maladry A, Lefever E, Van Hee C, et al. A Fine Line Between Irony and Sincerity: Identifying Bias in Transformer Models for Irony Detection. Proceedings of the 13th Workshop on Computational Approaches to Subjectivity, Sentiment, & Social Media Analysis. Published online 2023. doi:10.18653/v1/2023.wassa-1.28
86. Sundara Raman R, Shenoy P, Kohls K, et al. Censored Planet: An Internet-wide, Longitudinal Censorship Observatory. Proceedings of the 2020 ACM SIGSAC Conference on Computer and Communications Security. Published online 2020 Nov 2. doi:10.1145/3372297.3417883
87. Metaxa D, Park JS, Robertson RE, et al. Auditing Algorithms: Understanding Algorithmic Systems from the Outside In. Foundations and Trends® in Human–Computer Interaction. 2021;14(4):272-344. doi:10.1561/1100000083