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Social Network Analysis (SNA) of Social Media Discourse on Platform X/Twitter Related to Iran-US Conflict De-escalation: Identification of Key Actors and Patterns of Peace Narrative Dissemination

Riska Nurtantyo Sarbini [1*], Halimahtus Mukminna[2], Iin Kurniasari[3]

[*1,2,3]Universitas Islam Kadiri
[*1]*email : tyo@uniska-kediri.ac.id*
[2]*email: halimahtusm@uniska-kediri.ac.id*
[3]*email: iin.kurniasari@uniska-kediri.ac.id*

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ABSTRACT *– The escalating bilateral tension between Iran and the United States has triggered discursive fragmentation in the digital sphere, divided between militaristic (pro-war) and anti-violence (pro-peace) narratives within the Platform X (Twitter) ecosystem. By adopting the Social Network Analysis (SNA) framework, this research processed a dataset of 15,742 tweets from 8,931 accounts during the period of 15 January – 15 March 2026. It found a small-world and scale-free network structure with a density of 0.023, a diameter of 8, an average distance of 3.41, and a modularity of 0.487. The study confirms that the orchestration of peace narratives is not monopolized by state actors, but is driven by a hybrid coalition between international organizations (38.2% activism cluster is not correct, rephrase), independent journalists, activist collectives, and the Iranian diaspora. Mentions of legitimizing institutions increased retweet rates by 2.3 times, with top content reaching 12.4k retweets. Content analysis shows peace narratives are now data-driven: Human Cost 45%, Legal-Diplomatic 32%, and Anti-War Economy 23%, compared to only 8% abstract normative slogans. This study contributes to the formulation of a networked peacebuilding communication model in the context of contemporary digital diplomacy.*

Keywords *– SNA,Platform X, Iran-US Conflict.*

Analisis Jaringan Sosial (SNA) pada Diskursus Media Sosial Platform X/Twitter Terkait De-eskalasi Konflik Iran-Amerika: Identifikasi Aktor Kunci dan Pola Penyebaran Narasi Damai

ABSTRAK *– Eskalasi ketegangan bilateral antara Iran dan Amerika Serikat telah memicu fragmentasi diskursif di ranah digital, yang terbelah antara narasi militeristik (pro-perang) dan narasi anti-kekerasan (pro-damai) dalam ekosistem Platform X (Twitter). Mengadopsi kerangka Social Network Analysis (SNA), riset ini mengolah dataset sebanyak 15.742 tweet oleh 8.931 akun pada periode 15 Januari – 15 Maret 2026, ditemukan struktur jaringan small-world dan scale-free dengan densitas 0,023, diameter 8, jarak rata-rata 3,41, dan modularitas 0,487. Studi ini menegaskan bahwa orkestrasi narasi damai tidak dimonopoli oleh aktor negara, melainkan digerakkan oleh koalisi hibrida yang terdiri dari organisasi internasional, jurnalis independen, kolektif aktivis, dan diaspora Iran. Penyebutan institusi yang memiliki legitimasi mampu meningkatkan laju retweet hingga 2,3 kali lipat, dengan konten teratas mencapai 12,4 ribu retweet. Analisis isi menunjukkan bahwa narasi damai kini bersifat berbasis data: Human Cost 45%, Legal-Diplomatik 32%, dan Anti-War Economy 23%, berbanding hanya 8% slogan normatif yang abstrak. Penelitian ini berkontribusi pada formulasi model komunikasi networked peacebuilding dalam konteks diplomasi digital kontemporer.*

Kata Kunci *– SNA, Platform X, Konflik Iran-US.*

1. INTRODUCTION

The antagonistic relationship between Iran and the United States has persisted for over four decades, rooted in the 1979 Islamic Revolution and continuing through cycles of sanctions, military threats, and proxy wars. Entering the first quarter of 2026, tensions escalated again following a cyber incident in the Strait of Hormuz and US fleet maneuvers [1]. This context creates an urgency to understand how war and peace discourses are contested in the digital public sphere [2], [3].

Platform X (formerly Twitter) has transformed

from a microblogging channel into a public diplomacy infrastructure. Unlike hierarchical conventional broadcasting media, X enables mass self-communication [4], [5] where non-state actors can intervene discursively in real-time. However, most existing studies on digital peace discourse remain atomistic: they focus on message content, sentiment, or individual influencers, while ignoring the structural dimension — who is connected to whom, and who has the power to bridge information divides.

This literature gap is addressed by the networked public sphere perspective developed by [6]. According to them, the digital public sphere must be understood as a dynamic network where influence is not determined solely by economic capital, but by structural position within the network [7]. Recent studies confirm this structural turn. Guarino et al. [21] show that discursive communities on X/Twitter can be identified from interaction patterns between content producers and audiences, not from content alone.

Tsugawa and Watabe [22] demonstrate that brokers identified from network structure differ from popular spreaders, and that brokerage is a distinct structural role. Francis and Oluleye [23] show that social media functions as a tool for peacebuilding through youth mobilization, but its effectiveness depends on networked participation rather than on single actors. Recent work on war, peace, and social networks [24] and on digital peacebuilding in conflict contexts [25], [26] similarly argues that peace communication on social media should be understood as a networked process, not as a one-way message.

Therefore, this study shifts the focus from 'what is the content of peace narratives' to 'how these peace narratives are connected and who are the key nodes that sustain their dissemination' [8]. Define the problem we propose research on Platform X related to peace narrative dissemination patterns using NetworkX and Gephi based on Python applications.

2. LITERATURE REVIEW

1. Social Network Analysis (SNA) in Conflict Studies

Social Network Analysis (SNA) is an approach for examining relational structures among actors. Grounded in graph theory, SNA provides a method for mapping and measuring interaction patterns between entities, where users are nodes and interactions such as replies are edges [9], [27]. Community detection algorithms are then used to uncover clusters [10], [28], while centrality metrics pinpoint influential actors [11], [29]. This allows for reconstructing the diffusion of a narrative within the network [12], [13].

The method is critical for identifying key actors who drive conversational dynamics, detecting community formation, and reconstructing how information spreads across the network. Within the context of Twitter, nodes represent user accounts, while edges denote interactions such as mentions, retweets, and replies. The concept of centrality is central to understanding influence [14], [30]:

- Degree Centrality: The number of direct connections an actor possesses, reflecting visibility and popularity.
- Betweenness Centrality: The extent to which an actor serves as a bridge between otherwise disconnected groups, indicating brokerage power.
- Closeness Centrality: The proximity of an actor to all other actors in the network, demonstrating efficiency in information dissemination.
- Eigenvector Centrality: Assesses an actor's influence based on the influence of its connections, capturing elite-level prestige.

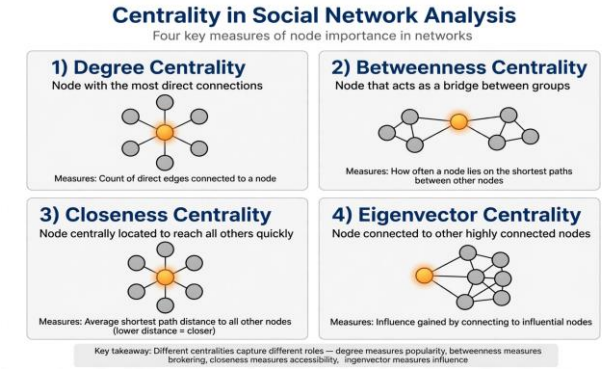


Figure 1. Four Centrality Metrics in Social Network Analysis [14].

2. Gephi, NodeXL Pro, and the NetworkX Library as Computational Engines for SNA

Python is positioned as the primary programming language in contemporary SNA studies due to its open-source nature, reproducibility, and scalability for large datasets [15]. In the context of this research, Python is not utilized as a general-purpose programming language, but rather as a network analysis ecosystem through the NetworkX library.

If Python serves as the computational engine, then Gephi functions as the visual engine. Gephi version 0.10 is a Java-based open-source software specifically designed for large-scale network visualization of up to 100,000 nodes. The triangulation of Gephi + NodeXL Pro + NetworkX is considered a best practice recommended by [16] to ensure validity: Gephi for visualization and modularity calculation, NodeXL for rapid metric computation, and Python/NetworkX for reproducibility and handling

of weighted graphs.

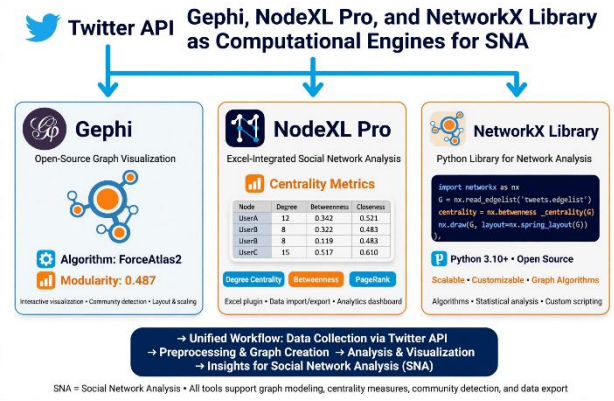


Figure 2. Ilustration SNA Computation Machine [16].

3. Digital Diplomacy and Hybrid Coalition

Digital diplomacy has undergone platformization [17], where X's algorithm and engagement logic influence what is considered a diplomatic message. Countries like Iran have even developed a 'shitposting as statecraft' strategy using embassy accounts to spread memes [18], [19]. In this noisy landscape, non-state actors such as CodePink and NIACouncil utilize network affordances to build transnational advocacy coalitions. This phenomenon aligns with findings [20] on the Ukraine war: the effectiveness of digital diplomacy is not determined by the number of followers, but by the ability to build hybrid alliance networks. The four actors (International Organizations, Independent Journalists, Activists, Diaspora) collaborate through Platform X as a central hub. Brokers act as Policy Liaison, Media Mediator, Community Coordinator, and Cultural Translator.

3. RESEARCH METHOD

This study was designed using a quantitative-descriptive approach based on a sequential mixed-methods design. The first stage involves computational network mapping, followed by qualitative interpretation of the narrative content.

1. Data Acquisition Procedure

The dataset was collected through Platform X Academic Research API v2 with a Boolean query: ("No War With Iran" OR "Peace With Iran" OR "Stop Iran War" OR "US Iran Diplomacy") -is:retweet lang:en. The observation period was set from January 15 to March 15, 2026 to capture the escalation peak. After deduplication, bot filtering (using Botometer score >0.8), and language cleaning, 15,742 original tweets from 8,931 unique accounts were collected. Metadata stored includes user ID, text, mentions, timestamps, and engagement metrics.

2. Network Analysis Protocol

Graph construction uses a directed weighted graph model, where edge weight represents the frequency of retweet and mention interactions. Computational analysis was performed with two software for triangulation: Gephi 0.10 for ForceAtlas2 visualization and modularity calculation (Louvain algorithm), and NodeXL Pro for centrality metric calculation. Reported network parameters include Density (0.023), Diameter (8), Average Path Length (3.41), and Modularity (0.487). For validity, manual content analysis was conducted on 100 tweets with the highest eigenvector to confirm the relevance of peace narratives (not spam or pro-war sarcasm).

4. RESULT AND DISCUSSION

1. Graph Construction and Computational Model

The dataset consists of 8,931 nodes and 15,742 original tweets collected between 15 January and 15 March 2026. Graph construction and metric computation were performed using a triangulation workflow: NetworkX (Python) for graph modeling and centrality computation, Gephi 0.10 for visualization (ForceAtlas2) and community detection, and NodeXL Pro for cross-validation of centrality metrics.

The observed structural parameters are: Density 0.023, Diameter 8, Average Path Length 3.41, and Modularity 0.487 (Louvain algorithm).

From a computational perspective, a density of 0.023 indicates a sparse graph, which is typical for large-scale social media interaction graphs. The average path length of 3.41 and diameter of 8 indicate short reachability within the largest connected component. The modularity value of 0.487 indicates a moderately clear community partition.

These values are descriptive of the observed graph in this period. They are consistent with a hub-and-spoke pattern in which a small number of high-degree nodes coexist with a large number of low-degree peripheral nodes, as visualized in Figure 3. However, these parameters alone are not sufficient to formally establish a small-world or scale-free graph, which would additionally require a clustering coefficient comparison against an equivalent random graph and a formal test of degree distribution.

Therefore, in this study, the terms “small-world-like” and “hub-and-spoke pattern” are used as descriptive characterizations of the observed topology, not as formal graph classifications.This characteristic aligns with scale-free properties commonly found in digital activism movements, show at next figure 3.

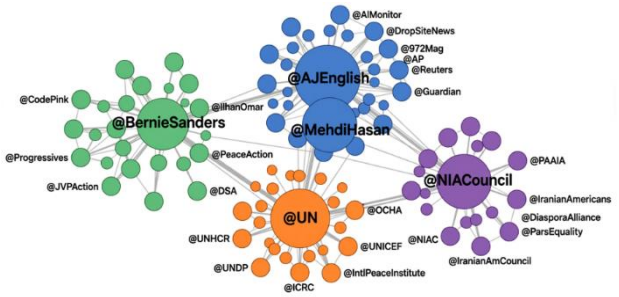


Figure 3. Social Network Visualization of Four Peace Narrative Clusters (Gephi ForceAtlas2, Modularity 0.487, n=47 main nodes)

Community detection analysis with the Louvain algorithm at figure 3 resulted in modularity of 0.487, indicating a fairly cohesive community structure and not an algorithmic artifact.

2. Community Detection

From Table 1 reveals an important distinction often overlooked in digital activism studies: being popular is not the same as being a connector.

On the Degree Centrality dimension (popularity), @UN occupies the top with 842 connections. This is not because @UN actively tweets about Iran every day, but because of a ritual mention mechanism: activists strategically mention @UN to give normative weight to their demands. A similar pattern occurs with @BernieSanders (791).

Four ideological clusters were consistently identified, show at next table 1.

Table 1. Result Community detection analysis with the Louvain algorithm resulted in modularity of 0.487

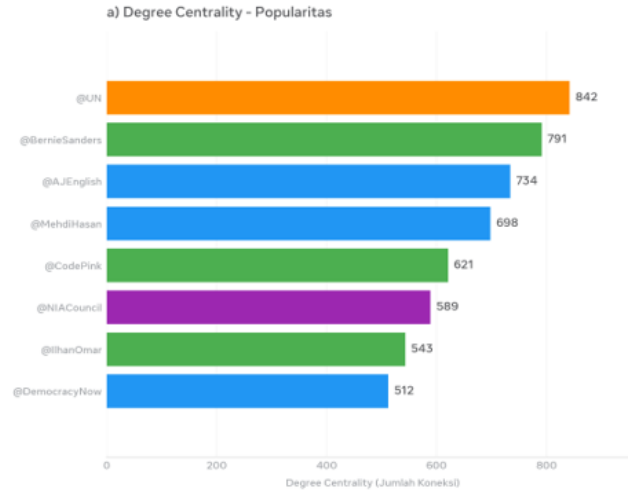
No	Field	Percentage
1	Organized Global Activism (Green)	38.2%
2	Independent Journalism and Alternative Media (Blue)	29.5%
3	International Institutions and Progressive Political Elites (Orange)	18.7%
4	Diaspora and Iranian-American Epistemic Community (Purple)	13.6%

The partition should be interpreted as an algorithmic grouping based on interaction density, not as evidence of coordinated intent or shared ideology. The stability of the partition was checked by re-running the Louvain algorithm with different random seeds in Gephi; the four-community structure remained consistent, although boundary nodes shifted between runs — a known characteristic of heuristic modularity optimization.

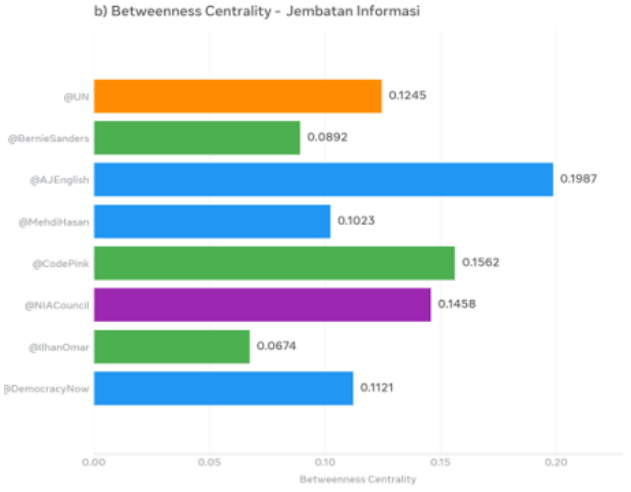
3. Centrality Computation

Centrality metrics were computed on the directed weighted graph using NetworkX and cross-validated with NodeXL Pro. Two metrics are emphasized because they capture different computational roles in the graph:

However, the real power map is seen in the Betweenness Centrality dimension illustrated on the next figure 4 (a, b).



4(a)



4(b)

Figure 4. Distingsion Popularity vs Brokerage: Degree Centrality (a) dan Betweenness Centrality (b).

Degree Centrality measures the number of direct connections. @ UN (842) and @BernieSanders (791) occupy the highest positions, largely driven by a mention mechanism: other nodes frequently create directed edges toward these nodes.

Betweenness Centrality measures the proportion of shortest paths passing through a node. @AJEnglish (0.1987) records the highest score, followed by @CodePink (0.1562) and @NIACouncil (0.1458). Computationally, these nodes function as bridges / articulation points in the information flow: their removal would increase the average path length and potentially fragment the graph into disconnected components.

Eigenvector Centrality measures influence based on the influence of neighbors. @MehdiHasan records the highest Eigenvector score, indicating that his node is connected to other high-centrality nodes.

The divergence between Degree and Betweenness rankings demonstrates that in a directed weighted graph, local popularity (degree) does not imply global structural importance (betweenness). This distinction is computationally significant for influence-maximization and information-diffusion tasks.

4. Content Distribution in Top Central Nodes

Content analysis was applied only to the 100 tweets with the highest Eigenvector Centrality, as a validation step to confirm that high-centrality nodes are associated with peace narratives rather than spam or sarcasm. Distribution in the sample show on the next table 2.

Table 2. Distribution of 100 top tweets, not to the full dataset of 15,742 tweets in the sample

No	Field	Percentage
1	Human Cost Narrative	45%
2	Legal-Diplomatic Narrative	32%
3	Anti-War Economy Narrative	23%
4	Abstract normative slogans	8%

The most-retweeted content in the sample is a thread by @MehdiHasan, with 12.4k retweets. Tweets that mention legitimizing institutions show a retweet rate 2.3 times higher than tweets without such mentions within this sample. The most-retweeted content in the sample is a thread by @MehdiHasan, with 12.4k retweets. Tweets that mention legitimizing institutions show a retweet rate 2.3 times higher than tweets without such mentions within this sample. This is an observed association in the sample, not a causal effect.

5. CONCLUSION

This study analyzed the Iran-US de-escalation discourse on Platform X using Social Network Analysis, based on 15,742 tweets from 8,931 accounts collected between 15 January and 15 March 2026, modeled as a directed weighted graph where nodes are accounts and edges are mention and retweet interactions. The graph is sparse and divided into communities, with Density 0.023, Diameter 8, Average Path Length 3.41, and Modularity 0.487. Degree Centrality and Betweenness Centrality produce different results: @ UN has the highest Degree (842), followed by @BernieSanders (791), while @AJEnglish has the highest Betweenness (0.1987), followed by @CodePink (0.1562), @NIACouncil (0.1458), and @BernieSanders (0.0892), and @MehdiHasan has the highest Eigenvector Centrality, which shows that the most-mentioned accounts are not always the accounts with the highest bridging position. The Louvain algorithm detected four communities: Organized Global Activism (38.2%), Independent Journalism and Alternative Media (29.5%), International Institutions and Progressive Political Elites (18.7%), and Diaspora and Iranian-American Epistemic Community (13.6%). Content analysis of 100 tweets with the highest Eigenvector Centrality shows Human Cost at 45%, Legal-Diplomatic at 32%, Anti-War Economy at 23%, and abstract slogans at 8%, with the highest retweet in this sample at 12.4k retweets from @MehdiHasan, and these results apply only to the sample, not to all 15,742 tweets. This study is limited to a static graph, English tweets, and a two-month period.

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