Analysis of Cross-Platform Narrative Dissemination Through Contextual Focal Structures

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Abstract. This study investigates how political discourse spreads across social media by identifying influential user groups, termed focal structures. We construct a cross-platform multiplex network linking users and narratives, and apply the Contextual Focal Structures Analysis (CFSA) algorithm to detect context-specific influence. Focusing on Taiwan's 2024 presidential election, we analyze 4,817 Instagram, 2,560 TikTok, 11,134 X, and 7,327 YouTube posts. Our findings reveal that influence often stems not from individuals but from coordinated or organically aligned groups shaping narratives across platforms. This work presents a scalable method for modeling narrative-driven influence, highlighting the importance of understanding cross-platform coordination in shaping political perceptions.

Keywords: Contextual Focal Structures, Multiplex Networks, Narrative Propagation, Influential Groups of Users, Social Media, Instagram, TikTok, YouTube, X/Twitter

1 Introduction

Social media platforms like Twitter, Facebook, Instagram, YouTube, and TikTok have revolutionized how information is created, shared, and consumed. With billions of users and low entry barriers, they offer unprecedented access to audiences, making them central to personal expression, activism, marketing, and political discourse. However, this openness also facilitates the spread of misinformation, disinformation, and strategic narratives, necessitating frameworks to analyze influence and information diffusion [15, 1].

The ease of account creation and algorithmic affordances encourage users to maintain identities across multiple platforms [12], allowing narratives to propagate fluidly between them. Understanding groups that coordinate such diffusion is critical, as these actors—ranging from grassroots to state-sponsored—play central roles in amplifying messages. Importantly, narrative spread often involves loosely connected users, making traditional user-user network analysis insufficient [6].

To identify influential actors, centrality measures help highlight key individuals, while group-level influence is better captured through algorithms like the Focal Structure Algorithm [16] and its extensions. Alassad et al. [5] introduced a bi-level optimization approach that balances local influence and global modularity, which later evolved into the Contextual Focal Structures Analysis (CFSA) model [4], capable of capturing influence across multiplex and contextual layers.

This study aims to extract and contextualize influential groups driving cross-platform narratives. Rather than isolating individual influencers, the goal is to uncover hidden, coordinated structures shaping public discourse. By focusing on structural and contextual dynamics, this research contributes to identifying influence campaigns and enhancing digital transparency.

2 Related works

The section discusses the scholarly related to the current study. Since our research is based on narratives, we begin our discussion from computational narratology and then present works done on identifying focal structures in social networks.

2.1 Computational Narratology

Narratives offer a powerful lens for analyzing large text corpora, particularly in dynamic environments such as social media. Over time, narrative extraction has shifted from manual techniques to automated, machine learning-based approaches [6], enabling the analysis of complex events such as the South China Sea dispute [8].

Recent advances in natural language processing—particularly large language models (LLMs) like GPT-4—have further enhanced this process. LLMs have been shown to generate and extract narratives effectively across contexts. Prior studies highlight their performance: Shakeri et al. [14] used GPT-3 for storytelling; Beguŝ [7] found GPT-4 produced richer, more diverse narratives; and Lynch et al. [11] reported that 87.43% of GPT-4 narratives matched the intent of structured prompts.

With its multimodal capabilities and proven performance, GPT-4 offers a robust and scalable solution for extracting narratives from unstructured, cross-platform social media data.

2.2 Identifying Focal Structures in Social Networks

Previous research has laid a strong foundation for identifying influential user groups in social media networks. Şen et al. [16] introduced the concept of "focal structure sets"—small groups capable of mobilizing public discourse—using a greedy algorithm to detect influence on platforms like Twitter and Facebook. Alassad et al. [5] further advanced this work with a bi-level optimization model that combined local centrality and global modularity to identify co-commenter groups spreading fake news on YouTube.

However, these methods primarily focus on unimodal user-user interactions, limiting their ability to account for contextual factors. To address this, Alassad and Agarwal [4] proposed the Contextual Focal Structures Analysis (CFSA) model, which incorporates multiplex networks to capture layered behaviors—such as user-user ties and hashtag co-occurrence—enhancing interpretability and contextual relevance.

Building on this, Akinnubi et al. [2, 3] introduced a Cartesian merge model that constructs multiplex networks across topic, entity, and document layers. Leveraging CFSA, they identified context-specific influential entities, demonstrating the model's adaptability across complex, heterogeneous data environments.

3 Data

This study focuses on the 2024 Taiwan Presidential Election, examining a multi-platform anti-disinformation campaign that emerged following the election results. The initiative reflects a "whole-of-society" effort to counter false information amid growing concerns about disinformation intended to delegitimize the election, particularly in the context of Taiwan's evolving democracy and ongoing tensions with China [10]. Social media played a central role in both spreading and countering misinformation, with fact-checking efforts becoming a key line of defense.

Data was collected through a multi-stage process across platforms. Initial seed posts were retrieved using keywords like #Taiwan and #TaiwanElection. These were expanded using co-occurring terms extracted from the seed dataset. To ensure relevance, GPT-4 was used to filter the data based on campaign context, retaining only posts aligned with the disinformation and counter-disinformation narratives.

The dataset includes both English and non-English posts. Non-English content was translated using the DeepL API[3]. We collected 4,817 posts from Instagram, 2,560 from TikTok, 11,134 from X, and 7,327 from YouTube related to the Taiwan 2024 election. These posts serve as the foundation for our cross-platform narrative analysis.

4 Method

This section presents the methods used in this research. Sections 4.1, 4.2, and 4.3 discuss the techniques used for extracting narratives, identifying focal structures, and creating the cross-platform narrative graph, respectively.

[3] https://www.deepl.com

4.1 Narrative Extraction

Narratives were extracted using the method proposed by Amure and Agarwal [6] and Gurung et al. [8], with a key modification: campaign context was explicitly introduced into the prompt fed to GPT-4. This enabled narrative extraction across multiple modalities, including text (X, YouTube transcripts, TikTok comments) and image-derived captions (Instagram). Built on the Transformer architecture, GPT-4 uses self-attention to capture long-range dependencies and contextual nuance. Prior studies support its narrative modeling capacity [14, 7, 11].

Let S, P, N_a, and U denote platforms, posts, narratives, and users, respectively. For each post $p \in P$ by user $u \in U$ on platform $s \in S$, we extracted a narrative $n \in N_a$. We applied two filters: (1) polarity mismatch between post and narrative, and (2) contextual inconsistency. Contextual filtering was done using a similarity check described in Section 4.3.

4.2 Contextual Focal Structure Analysis (CFSA)

The Contextual Focal Structure Analysis (CFSA) algorithm identifies influential groups in a multiplex network by integrating structural and contextual signals across three layers: user-user, user-narrative, and narrative-narrative. Unlike traditional approaches focused on direct interactions, CFSA captures cross-layer influence and coordinated behavior by optimizing centrality and modularity in two stages.

At the node level, the algorithm selects locally influential users by maximizing the joint influence from all layers:

$$\max \sum_{i=1}^{n} \sum_{j=1}^{m} \left(\delta_i^{UU} \oplus \rho_{ij}^{UH} h_j^{HH} \right) \tag{1}$$

Here, δ_i^{UU} is the user centrality in the user-user layer, ρ_{ij}^{UH} the user-narrative connection strength, and h_j^{HH} the centrality of narrative j in the narrative-narrative layer. The operator $\oplus$ fuses influence across layers. Constraints ensure selected users contribute strongly to both local cohesion (e.g., clustering) and network-level metrics like modularity.

At the group level, CFSA refines the selected user sets using spectral modularity optimization:

$$\max \sum_{j=1}^{k} e_j^q, \quad \text{where} \quad B = A - gg^T \tag{2}$$

Here, e_j^q represents modularity contribution from each group, A is the adjacency matrix, and g is the degree vector. Redundant or overlapping groups are filtered out, and final group selection ensures structural sparsity and contextual relevance.

CFSA thus produces a set of contextual focal structures—cohesive user-narrative groups that reveal how influence and coordination unfold across platforms and topics. For theoretical foundations and proofs, see [4, 2, 3].

4.3 Cross-Platform Narrative Graph

To support the CFSA, we construct a multiplex network that captures contextual relationships among narratives and users across platforms. This network integrates three layers:

- **User-User Layer:** Connects users posting similar narratives.
- **User-Narrative Layer:** Links users to their narratives.
- **Narrative-Narrative Layer:** Connects semantically related narratives.

A key step is defining inter-narrative similarity through an aggregate connectivity score S, combining semantic and entity-level similarity:

$$S(n_1, n_2) = \frac{s_1(n_1, n_2) + s_2(n_1, n_2)}{2} \tag{3}$$

Here, s_1 is the cosine similarity between narrative embeddings extracted using the transformer-based `all-mpnet-base-v2` model [13], which captures sentence-level semantics. s_2 is the Jaccard similarity over named entities extracted via SpaCy [9]:

$$s_2 = \frac{|E_i \cap E_j|}{|E_i \cup E_j|} \tag{4}$$

Narratives n_1 and n_2 are connected if $S(n_1, n_2) \geq 0.5$. Given posts p_1 and p_2 by users u_1, u_2, and narratives n_1, n_2, we construct:

$$G = (V, \{E_l\}_{l=1}^{3}),$$

where V includes all users and narratives, and E_l defines edges for each of the three layers. Users u_1, u_2 are connected if their posts yield similar narratives; each user u is linked to their narrative n; and narratives n_1, n_2 are connected based on the score S. This structure captures influence and coordination across platforms, without requiring explicit user identity matches.

5 Result and Discussion

Ten focal structures were identified across two major discussions; for brevity, we highlight one representative from each.

Focal Structure 5 (Figure 1) illustrates how users shaped Taiwan's 2024 election discourse across YouTube, X, TikTok, and Instagram. While YouTube narratives emphasize democratic progress, X highlights the DPP's parliamentary setbacks, and Instagram underscores geopolitical tension with China. These

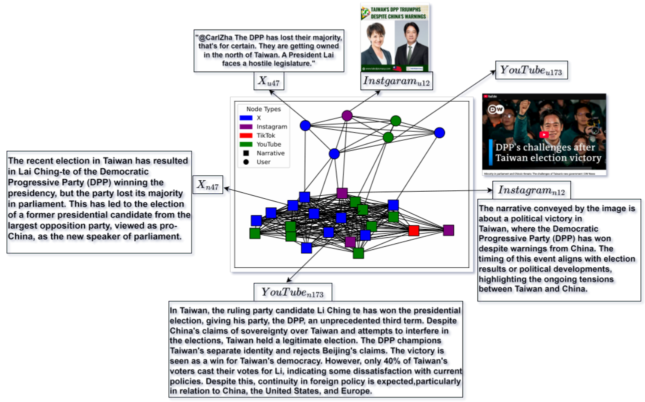

Fig. 1. Network showing the relationship between narratives and users on different platforms in focal structure 5 for TC. n refers to narrative id and u refers to the user id.

platform-specific framings suggest strategic adaptation by users to engage different audiences. Whether coordinated or emergent, the discourse consistently touches on electoral legitimacy, policy direction, and Taiwan-China relations.

Focal Structure 16 (Figure 2) captures a pro-China narrative propagated via Instagram and TikTok. On Instagram, China's Taiwan Affairs Office contests the DPP's legitimacy, while TikTok posts frame Taiwan as provoking conflict. This narrative alignment across platforms suggests an effort to shift blame onto Taiwan and reinforce China's geopolitical stance, influencing both domestic and international perceptions of regional stability.

6 Conclusion

This study examined how political discourse gains traction across social media by focusing on influential user groups, termed focal structures. We constructed a cross-platform multiplex network linking users and narratives, and applied the CFSA algorithm to extract context-specific influential groups from the Taiwan 2024 election campaign.

Narratives on social media often emerge from loosely connected posts by diverse users, making their propagation difficult to trace. Our method addresses this by modeling narrative flows and identifying coordinated user groups that drive them. Findings show that influence is not confined to prominent individuals but often arises from groups shaping narratives in strategic, context-aware ways. As cross-platform information flows continue to influence public perception, scalable methods like ours are essential for understanding and responding to coordinated influence in digital ecosystems.

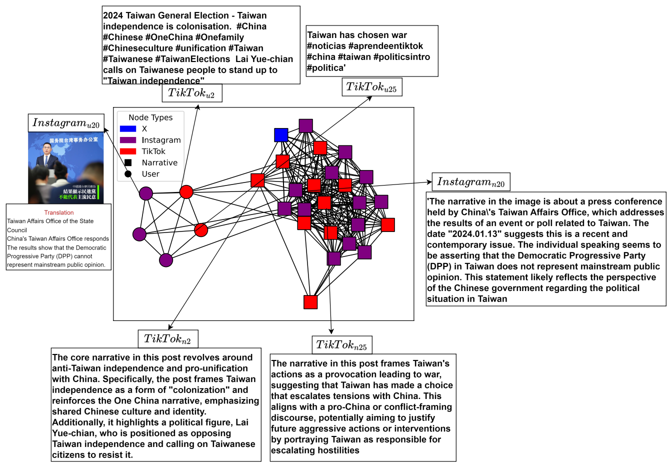

Fig. 2. Network showing the relationship between narratives and users on different platforms in focal structure 16 for TC. n refers to narrative id and u refers to the user id.

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