

Analyzing TikTok's Role in Mobilizing Dynamics for Information Campaigns during Taiwan's 2024 Elections

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Abstract

This research investigates and identifies the key mobilizing characteristics in contemporary online information campaigns using novel multi-method socio-computational techniques. Utilizing social theories and network science to study social process, we leveraged Diffusion of Innovations (DOI) theory to extract key mobilization elements at different stages (initialization, amplification, sustainment) of mobilization process from social network (TikTok). We identify and analyze mobilization characteristics of disinformation and anti-disinformation campaigns during Taiwan's 2024 presidential elections. Our investigation delves into dataset comprising 343 TikTok videos, 46,551 comments, 2,955 co-commenter nodes, and their 25,830 edges. Findings reveal that campaigns' successes hinge on audience engagement rather than rapid initiation or content volume. Notably, the network cohesion and topical stance of anti-disinformation co-commenters during the amplification stage played a crucial role in countering disinformation. This comparative analysis highlights the significance of understanding the mobilization process for a comprehensive view of online information campaigns.

Keywords: Mobilization, Elections, Co-commenters, Networks, Disinformation, Anti-disinformation.

1. Introduction

On January 13, 2024, Taiwan elected a new president. However, disinformation regarding the election persisted post-election, with rumors emerging shortly after alleging rigged voting or counting processes, along with narratives that pro-China candidate Ko Wen-je should have won the elections if there was not vote-rigging. In response, Taiwan's civil society, social network users, and government effectively countered these disinformation narratives by defending the election's transparency, successfully

diffusing their information operation within a week (*How Taiwan Beat Back Disinformation and Preserved the Integrity of Its Election | AP News, 2024*).

Social networks played a significant role in these elections, with platforms like TikTok and YouTube transforming political communication by enabling rapid online mobilization (Lipschultz, 2022). Online mobilization involves using digital platforms to organize, coordinate, and engage participants in collective actions for information dissemination. Analyzing online social campaign mobilization characteristics through social science theories, such as the Diffusion of Innovations (DOI) theory, is essential. DOI theory outlines stages—initialization, amplification, and sustainment—describing how new ideas or information spread within society. Understanding information flow in these stages reveals how information campaigns or social movements gain traction online, and ultimately provide indicators of a campaign's success or failure (Rogers et al., 2014; Shaik et al., 2023; Shaik, Cakmak, et al., 2024).

The pervasive impact of disinformation campaigns on democratic processes is a global concern, with Taiwan's elections exemplifying how online actors such as commenters and content generators can manipulate social media to influence public opinion and electoral outcomes. Disinformation campaigns can undermine trust in electoral processes, distort public discourse, and polarize societies (Tucker et al., 2018). Conversely, anti-disinformation efforts are crucial for safeguarding information integrity, promoting transparency, and maintaining the democratic fabric (Pennycook et al., 2020). Taiwan's elections serve as a critical reference, illustrating the spread of rumors about vote manipulation and society's efforts to counter these rumors, which provide lessons for other countries holding elections. Studying these phenomena is vital for developing strategies to counteract false narratives and ensure

democratic resilience. This study aims to identify and examine the mobilizing characteristics of disinformation and anti-disinformation campaigns, particularly on TikTok, due to its popularity in Taiwan. The research focuses on identifying key mobilizing patterns from disseminated content and engagements using DOI and network perspectives, delineating the mobilization characteristics inherent in these campaigns and addressing our research question:

Research Question: What are the key mobilization characteristics of disinformation and anti-disinformation campaigns on TikTok during Taiwan's presidential elections?

In the following section, we present our theoretical framework based on previous research on disinformation and anti-disinformation campaigns, the diffusion of innovations theory, online mobilization, and the role of commenters on social networks. These steps clarify the research methodologies adopted in this case study.

2. Theoretical Framework

This section provides the extant literature on this study and the theoretical layout to examine the research question.

2.1. Disinformation and anti-disinformation campaigns

Studies have demonstrated that disinformation campaigns frequently exploit sensationalism and emotional appeals to quickly capture attention and disseminate misinformation (Tucker et al., 2018). These campaigns strategically deploy false information and multimedia (e.g., images, videos, and sidecars) contents to sway public opinion, undermine democratic processes, and incite social discord (Agarwal, 2023). They are often highly organized, employing bots and trolls to amplify their messages and extend their reach (Ferrara et al., 2016; Agarwal et al., 2017; Khaund et al., 2021). Conversely, anti-disinformation campaigns strive to counter these efforts by disseminating factual information, debunking myths, and promoting media literacy. Research suggests that effective anti-disinformation campaigns typically involve collaboration between governments, social media platforms, and fact-checking organizations (Howard & Hussain, 2011; Posetti et al., 2019). These campaigns employ various tactics, such as real-time fact-checking, transparency reports, and public awareness initiatives, to mitigate

the effects of false information (Pennycook et al., 2020).

2.2. Diffusion of Innovations (DOI) theory and its connection to social media campaigns and mobilization

The Diffusion of Innovation (DOI) theory, developed by Everett Rogers, elucidates how new ideas and technologies proliferate within a society. This theory is particularly pertinent to social media campaigns, as it provides a framework for understanding the dissemination and adoption of information by users. According to DOI theory, the adoption process is influenced by factors such as the perceived attributes of the innovation, communication channels, time, and the social system (Rogers et al., 2014). In the context of disinformation and anti-disinformation campaigns, DOI theory can be utilized to analyze how information rapidly spreads through social networks and how corrective information can be disseminated effectively. For instance, early adopters of disinformation might play a crucial role in setting trends, while opinion leaders in anti-disinformation efforts can aid in spreading accurate information and counteracting false narratives (Valente & Rogers, 1995). Several studies have examined the role of multimedia and co-occurring words in the DOI stages in online social movement mobilization process, which resembles the curves shaped like the letter 'S'. These curves demonstrate how certain categories of content (such as sidecars or conative words) or the engagement on the contents can influence the outcomes of a campaign's success in mobilization processes at different DOI stage (Shaik, Cakmak, et al., 2024; Shaik et al., 2023; Shaik, Yousefi, et al., 2024; Spann et al., 2022).

2.3. Role of social networks and co-commenters in mobilization

The role of social networks in the mobilization process has become increasingly significant, particularly in the context of political communication and information dissemination. Platforms like TikTok and YouTube have transformed the landscape, enabling rapid online mobilization and engagement (MacKinnon et al., 2021). Research indicates that social networks facilitate the rapid spread of both disinformation and anti-disinformation content by leveraging the interconnected nature of users. These platforms provide various affordances, such as sharing, commenting, and liking, that enhance the reach and impact of information (Schirch, 2021).

Commenters, or co-commenters, play a crucial role in this process. Co-commenters are individuals who engage with the same multimedia content, thereby forming implicit networks based on their interactions. These networks can be analyzed to understand the dynamics of information spread and the mobilization characteristics of different campaigns (Alassad et al., 2022). Co-commenter networks can significantly influence the mobilization process. For instance, in disinformation campaigns, co-commenters often work in a coordinated manner to amplify false narratives, creating an illusion of widespread agreement and thereby swaying public opinion. In contrast, in anti-disinformation campaigns, co-commenters help disseminate corrective information and debunk myths, often guided by opinion leaders who play a pivotal role in influencing other users (Gomes Ferreira et al., 2020).

The structural integrity and cohesion of these co-commenter networks can be assessed using network science techniques, such as measuring modularity and internal cluster density. High modularity and strong internal cluster density indicate tightly knit communities that can efficiently mobilize and sustain engagement over time (Kent, 2016; Mishra et al., 2008). These metrics are particularly relevant in multiple stages of the DOI model, where the objective is to maximize the spread and impact of information. Understanding the role of co-commenters in the mobilization process of social networks provides valuable insights into how information campaigns operate to mobilize and influence public opinion.

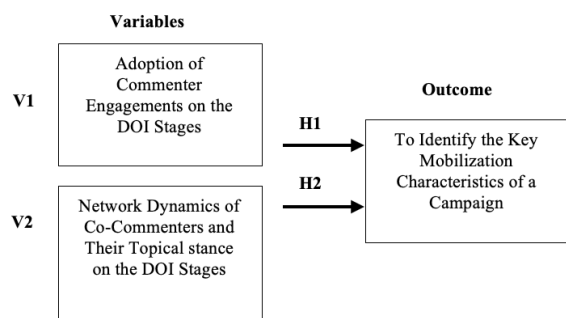


Figure 1. Research model diagram

In this research, we use the above-mentioned theoretical framework that encompasses social and network science theories as a guide to construct a research model with the following hypotheses aimed at answering our **Research Question**: to identify the key mobilization characteristics of a campaign, as illustrated in Figure 1.

H1: The adoption of commenter engagements varies across different DOI stages and is a key factor in identifying the mobilization characteristics of a campaign.

H2: The network dynamics of co-commenters and their topical stance across DOI stages significantly contributes to identifying the mobilization characteristics of a campaign.

3. Research Methodologies

This section presents our research design such as data collection and analytical approaches.

3.1. Data

To empirically examine the research question, TikTok data was collected from two distinct social movement campaigns that took place between January 12, 2024, and January 21, 2024, in Taiwan. These campaigns arose in the context of the 2024 Taiwanese presidential elections and are categorized as the ‘Disinformation’ and ‘Anti-disinformation’ campaigns. The disinformation campaign began to gain traction on January 12, 2024, the day preceding the presidential election, by disseminating rumors that cast doubt on the election process. Starting from January 13, 2024, the campaign flooded TikTok with edited and misleading videos that alleged voter fraud and vote rigging, aiming to undermine trust in the election results. Conversely, the anti-disinformation campaign commenced on the night of the voting, actively countering the disinformation narrative by sharing videos that elucidated the vote-counting process and presenting debunked evidence sourced from the ‘Taiwan FactCheck Center’.

Table 1. Collected data details

Campaigns	Time frame	Posts	Comments	
Disinfo	Jan 12, –Jan21, 2024	223	23,200	Likes = 133,273
				Replies = 7,142
Anti-disinfo	Jan 13, –Jan21, 2024	120	23,351	Likes = 362,863
				Replies =13,489

Data for both campaigns were gathered using Taiwanese key phrases identified from news articles and the ‘Taiwan FactCheck Center,’ utilizing the Apify scraper (<https://apify.com/>) for data crawling.

The translated key phrases for the disinformation campaign included: ‘electoral fraud,’ ‘manipulation,’ ‘vote rigging,’ ‘fraud,’ and ‘unfair practices.’ For the anti-disinformation campaign, the phrases included: ‘transparent,’ ‘fact-check,’ ‘verification,’ ‘credible elections,’ and ‘reject misinformation.’ Following data collection, the data was manually and qualitatively inspected to ensure accurate classification for each campaign, as detailed in Table 1. Then we translated Taiwanese texts from video titles and comments into English using DeepL translate API (*Translate Text | English | DeepL API Docs*, 2024).

3.2. Multi-Method Approach

The analytical process involved the analysis of disseminated content and engagements from both the DOI and network perspectives. In step 1, we generated the posting frequency of the videos and calculated the average engagement metrics to understand the posting and engagement dynamics for both campaigns.

For the comments-level analysis in step 2, we applied the S-curve logistic function to map the temporal cumulative frequency into three stages of the Diffusion of Innovations (DOI) model—initialization, amplification, and sustainment—based on the rate of change in the comments over the period for each campaign. This method enabled us to track the adoption of comments and determine whether the adoption of comments was in the initialization stage (when innovators first experiment with new ideas and technologies), the amplification stage (when early adopters, an early majority, and a late majority each adopt new ideas at different rates within their social systems), or the saturation stage (when it has reached a critical mass, thereby sustaining the movement and seeing a decrease in new adopters).

The logistic function is defined as:

$$f(t) = \frac{K}{1 + e^{-r(t-t_0)}} \quad (1)$$

where:

- $f(t)$ is the cumulative frequency at time t .
- K is the carrying capacity, representing the maximum value of $f(t)$ as t approaches infinity.
- r is the growth rate, which determines how quickly the adoption spreads.
- t_0 is the inflection point, the time at which the cumulative frequency reaches half of the carrying capacity K .

In step 3, we applied step 2 to the engagements (likes and replies) on the comments to understand overall commenters’ commenting and engagement behavior in the mobilization process according to DOI stages both in steps 2 & 3.

Based on step 2 & 3, our assessment identified specific periods of heightened engagement for both campaigns, as shown in Figure 4. The selection process is explained in the Results section:

- Disinformation – Initialization from January 12 to 13, 2024. Amplification from January 14 to 19, 2024. Sustainment on January 20 to 21, 2024.
- Anti-disinformation – Initialization from January 13 to 16, 2024. Amplification from January 17 to 19, 2024. Sustainment from January 20 to 21, 2024.

In step 4, we generated co-commenter networks for the campaigns and their identified stages, such as initialization and amplification, except for the sustainment stage due to no activity in that stage for both campaigns. Co-commenter networks help push content to viewers with the help of recommendation algorithms, thereby enhancing mobilization. Undirected co-commenter networks were built based on the following conditions using Gephi.

Where, $G = (V, E)$ represents the graph. (2)

- Nodes: Each node represents an individual commenter. V denotes the set of all nodes.
- Edges: An edge between two nodes is connected if the number of videos commented on by both nodes exceeds one video. An edge $(u, v) \in E$ exists if: $w_{uv} > 1$.
- Weighted Edges: The edges are weighted based on the number of videos on which both commenters have commented.
 w_{uv} = number of common videos commented on by both u and v .

In step 5, we calculated the modularity of each graph to evaluate the structural strength of each network with the Louvain algorithm (Blondel et al., 2008). The values are presented in Table 2. Additionally, in the same step, we identified the clusters with over 5% network spread for further analysis i.e., a cluster should have at least 5% of nodes in the entire network, and clusters with less than 5% of nodes were not considered for further analysis (Breznik, 2016). This selection was performed to pick the clusters that are larger in size, and we calculated the strength of internal cluster density using the following formula (Bartelmann et al., 2013):

$$D = \frac{\text{Number of Actual Edges}}{\text{Maximum Number of Possible Edges}(n*(n-1)/2)} \quad (3)$$

Lastly, we calculated the average of the overall internal cluster density, as shown in the Table 3. Steps 4 & 5 help to understand the structural dynamics of the co-commenter networks in the mobilization process as per the campaign.

From the identified clusters, we also extracted the prominent topics for each cluster based on the top 5 videos that have highest average engagement ratio and labeled them accordingly in Figures 5, 6, 7, and 8, along with the cluster numbers for readability.

Finally, in step 6, we extracted the comments from the top 5 identified videos in each cluster and analyzed the overall stance of the participated commenters using the instructive AI called LLaMA-3, 70B model (*Meta-Llama/Meta-Llama-3-70B Hugging Face*, 2024). A total of 4,239 comments were extracted from both campaigns. For stance detection, we used the following prompt, finalized after both disinformation and anti-disinformation articles collected from 'Taiwan FactCheck Center' and News Agency were fed to AI to extract indicators as per the campaign:

...

Anti-Disinformation Campaign Indicators

- * Statements supporting transparency and accountability in electoral processes.
- * Advocacy for fact-checking and verification as a response to claims.
- * Expressions of support for democracy, fair elections, and credible information.
- * Criticism of misinformation and promotion of factual integrity.
- * Phrases like "transparency", "fact-check", "verification", "credible elections", "reject misinformation".
- * Recognition of foreign influence operations, especially in the context of elections.
- * Discussion of the resilience of democratic systems against disinformation.
- * Use of advanced technology to identify and mitigate foreign disinformation efforts.
- * Highlighting the role of fact-checking organizations and investigative journalism in uncovering disinformation campaigns.
- * Statements supporting international cooperation to combat disinformation.
- * Emphasis on public awareness and education regarding misinformation and disinformation.
- * Community and Unity: community, together, unite, collaborate, solidarity.
- * Suggestions for improvement to avoid controversy.

Disinformation Campaign Indicators

- * Claims suggesting electoral fraud or manipulation without substantiated evidence.
- * Expressions of distrust towards electoral processes or outcomes.
- * Negative sentiment toward entities without basis, often involving foreign influence or conspiracy theories.
- * Use of charged or misleading statements to provoke distrust or fear.
- * Phrases like "vote rigging", "fraud", "unfair practices", "manipulated results", "pro-China", "CCP influence".
- * Pro-China narrative.
- * Use of edited or selectively cut videos to misrepresent the truth or to create a misleading narrative about electoral processes.

- * Spreading of claims that intentionally cause confusion about vote counting procedures, exploiting errors for malicious purposes.
- * Circulation of content that implies misconduct without showing the full context, often using digital platforms to enhance reach and impact.
- * Assertions made in the disinformation content that are promptly debunked by official verification centers yet continue to be promoted to stir public distrust.
- * Misrepresentation of the purpose and use of election-related materials, like ballot bags, to imply hidden agendas.
- ...

We also performed manual labelling on 230 comments from 3 random clusters for comparative evaluation and found AI labeling to be 0.93 accurate. This process helps to understand the overall stance of the major information drivers in a network that, to influence the public opinion, mobilizes in groups during its information campaign operations.

4. Results

In this section, we focus on analyzing our research question to analyze and identify the key mobilization characteristics of disinformation and anti-disinformation campaigns.

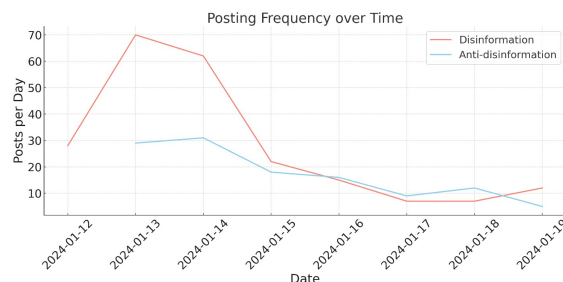


Figure 2. Video posting frequency

The disinformation campaign trend in Figure 2 shows a higher intensity of posting and burst pattern with high posting on January 13, 2014, peaking around 70 posts per day. This indicates a concentrated effort to spread information rapidly within a short timeframe to influence public perception quickly. In contrast, the anti-disinformation chart suggests a more sustained effort over several days aimed at gradually countering disinformation over time. These characteristics suggest different strategic approaches between the two campaigns. The disinformation campaign relies on a high-impact, short-term strategy to quickly influence public opinion, while the anti-disinformation campaign adopts a more measured, sustained approach aimed at long-term credibility and engagement. Figure 3 shows the anti-disinformation campaign posts significantly outperform the disinformation campaign in terms of engagements such as diggCount (Likes), with an average count of nearly 10,000 compared to approximately 2,500 for disinformation. The average PlayCount for anti-disinformation content is

significantly higher, with values nearing 300,000 compared to about 70,000 for disinformation content. Although shareCount and collectCount are lower compared to diggCount and PlayCount, the anti-disinformation campaign still leads in shareCount and collectCount, indicating that users shared and saved content related to countering disinformation.

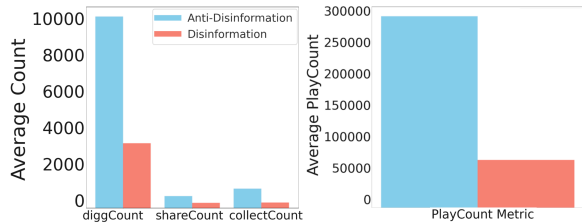


Figure 3. Average engagement on videos

This suggests that videos from the anti-disinformation campaign were positively received and showed strong approval from the audience. It also demonstrates its effectiveness in mobilizing public support and action successfully in countering disinformation. While disinformation content was high in volume, it did not resonate as positively or actively with viewers compared to anti-disinformation content that achieved widespread and impactful mobilization. This indicates the audience skepticism or resistance to disinformation content. The next analysis presents the reaction from commenters via the lenses of DOI stages of mobilization and presented results for **H1**. Figure 4 shows the adoption of comments in percentages over the DOI stages. The disinformation campaign accumulates comments more rapidly initially, similar to their posting frequency and surpassing the anti-disinformation campaign in early engagement.

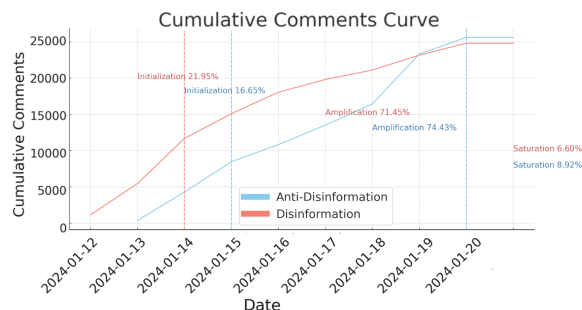


Figure 4. Cumulative comments frequency over DOI

However, comments adopted during the amplification phase for both campaigns are almost equal, which indicates more audience participation and discussion, suggesting that the audience were active during the critical period of the mobilization.

So, we expanded our investigation further to analyze the engagement behavior on comments over stages of mobilization.

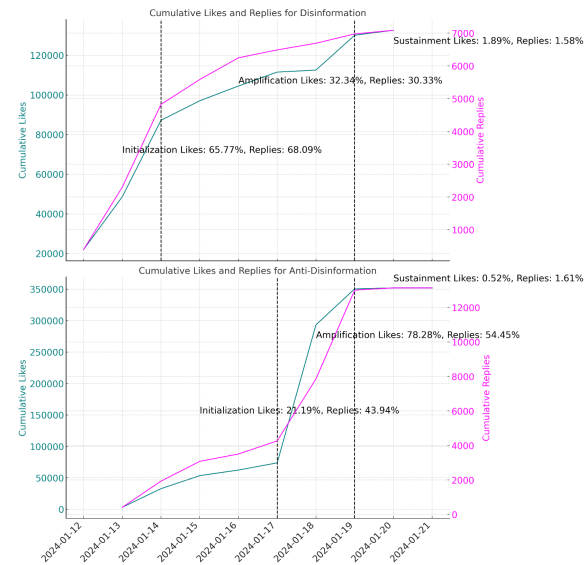


Figure 5. Cumulative likes and replies frequency over DOI

Unique pattern emerged in Figure 5. The cumulative likes and replies for the anti-disinformation campaign are significantly higher than those for the disinformation campaign. The anti-disinformation campaign reaches over 350,000 cumulative likes and over 12,000 cumulative replies, whereas the disinformation campaign peaks at about 120,000 likes and 7,000 replies. This highlights a more substantial and positive interactive audience response to the anti-disinformation content. The disinformation campaign shows early momentum with high initial engagement, but the anti-disinformation campaign demonstrates sustained growth, particularly during the amplification phase. The overall higher engagement for the anti-disinformation campaign suggests effective counter-mobilization strategies that resonated well with the audience. This might include clear, credible messaging and the use of fact-checking resources, which helped in sustaining engagement and countering the spread of disinformation effectively.

This intriguing pattern from Figure 5 inspired us to delve deeper into commenter behavior and their stance from a network perspective to discuss results for **H2**, as high interaction occurred during these periods. Commenters often appear in groups during online information campaign operations. While we cannot conclusively prove that these commenters are connected outside the online domain, they undoubtedly share a relationship within online

platforms, forming an implicit connection through various affordances available on social media. In our research, these commenters were connected based on the videos they commented on together. We refer to them as co-commenters and generated co-commenter networks to analyze their interactions and the dynamics of their collective behavior. This approach allows us to uncover the underlying structure and influence patterns within these online communities, providing valuable insights into how information is propagated and received during campaign operations.

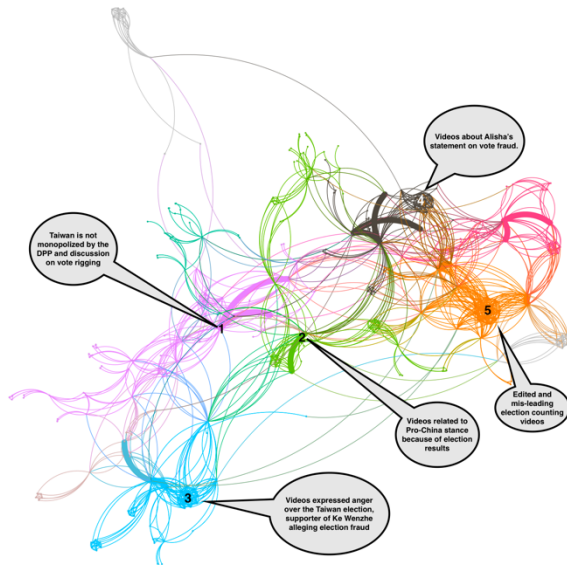


Figure 6. Disinformation co-commenter network initialization stage

All co-commenter networks according to their campaigns are shown in Figures 6, 7, 8, and 9. We identified a total of 2,573 unique co-commenters across both campaigns with 1,682 commenters in the disinformation campaign spread across 10 clusters, and 891 commenters in anti-disinformation campaign, spread across 8 clusters. Interestingly network visualizations reveal diverse topic themes and patterns that are labeled accordingly. **Initial stage disinformation networks propagated narratives of voter fraud and dissatisfaction with the election process, whereas amplification stage networks concentrated on alleging systematic issues and expressing anger over perceived electoral injustices. Initial stage anti-disinformation networks focused on contesting disinformation humorously and promoting democracy, while amplification stage networks highlighted the transparency of the election process and countered viral disinformation videos.**

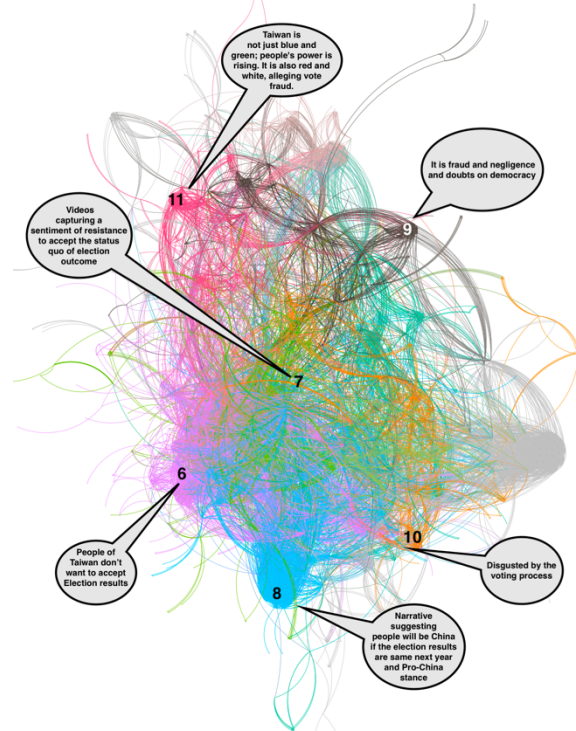


Figure 7. Disinformation co-commenter network amplification Stage

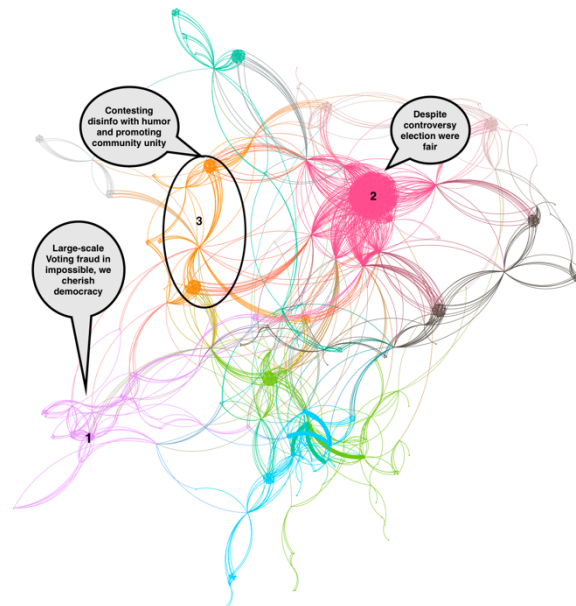


Figure 8. Anti-disinformation co-commenter network initialization stage.

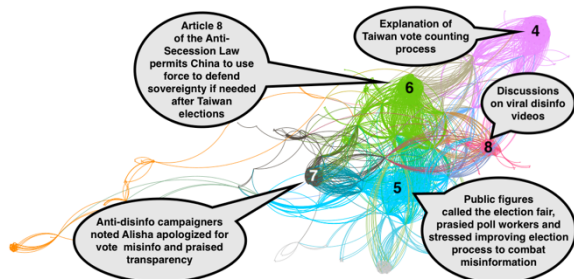


Figure 9. Anti-disinformation co-commenter network amplification Stage

Next, our analysis explores the network strength using the modularity measure and cluster strength using internal cluster density. This examination sheds light on the mobilization process by highlighting how tightly knit these communities are, the cohesion within clusters, and the overall structural integrity of the networks. By understanding these dynamics, we can better grasp the mechanisms through which these groups form, mobilize, and propagate their respective narratives within the digital landscape.

Table 2 shows the scores range is between -1 and 1, and observed modularity scores indicate a stronger community structure in initialization stages for both campaigns because of high positive value close to 1. In the amplification stage, community structure is not as strong as the initialization stage, but the anti-disinformation commenter network shows stronger structure than the disinformation campaign. This suggests that anti-disinformation networks were more tightly knit and engaged throughout the campaign duration.

Table 2. Modularity scores as per DOI stages

Campaigns	Initialization	Amplification
Disinformation	0.703	0.595
Anti-Disinformation	0.739	0.671

Table 3. Average cluster internal density as per DOI

Campaigns	Initialization	Amplification
Disinformation	0.274	0.152
Anti-Disinformation	0.242	0.450

Table 3 shows cluster internal density for disinformation campaigns decreased from the initialization (0.274) to the amplification stage (0.152), indicating a dispersal of network cohesion over time, signifying the weakening of the

disinformation commenter community. In contrast, anti-disinformation campaigns saw an increase in internal density from the initialization (0.242) to the amplification stage (0.450), reflecting a consolidation of network efforts and tighter community engagement as the campaign progressed.

Next, set of analyses focuses on identifying the topical stance of these co-commenters from their comments in these networks, to analyze their engagement patterns in mobilization stages as shown in Figures 9 and 10. A total of 4,239 comments were extracted, with 3,196 comments belonging to the disinformation campaign and 1,043 comments belonging to the anti-disinformation campaign.

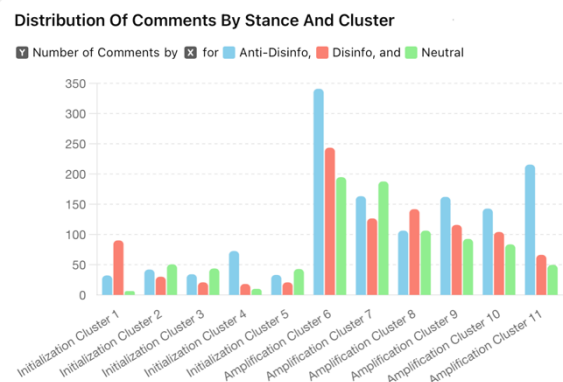


Figure 9. Disinformation comments' stance

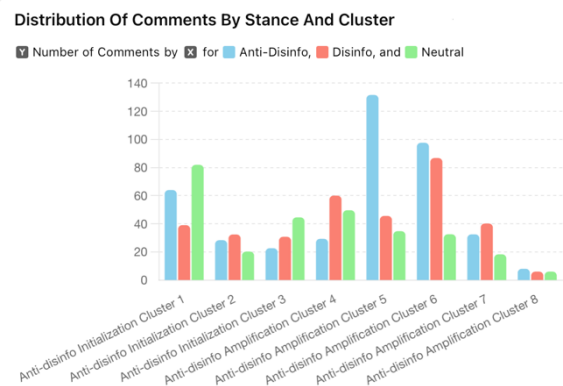


Figure 10. Anti-disinformation comments' stance

The stance detection analysis revealed distinct engagement patterns across different DOI stages. Interestingly, comments with an anti-disinformation stance were high overall but higher during the amplification stages compared to the initialization stages in both campaigns. In contrast, comments with a disinformation stance were consistently prominent in all stages of both campaign but never dominant, except in a few clusters: Cluster 1 and Cluster 8 in the

disinformation campaign, and Cluster 4 and Cluster 8 in the anti-disinformation campaign.

Following are the example comments along with their stance detected using LLaMA-3.

- Texts exhibiting characteristics of anti-disinformation stance: “The Central Election Commission has investigated and found no wrongdoing” (*expresses support for democracy, fair elections, and credible information*).
- Texts exhibiting characteristics of disinformation stance: “This president who has won by cheating in the election, what hope is left for us?”.
- Texts exhibiting characteristics of neutral stance: “What’s the privacy issue with anonymous voting?” (*raises a question without taking a stance*)

5. Conclusion and Future Directions

Our multi-method analysis, utilizing social and network science theories for comparative analysis, has yielded insights on the mobilizing characteristics of disinformation and anti-disinformation campaigns related to Taiwan’s 2024 presidential election on TikTok. The analysis reveals that the disinformation campaign efforts relied on atomic, high-volume bursts of content to create an immediate impact. In contrast, anti-disinformation strategies benefit from sustained, credible engagement that builds trust and fosters long-term interaction. This finding underscores the importance of mobilizing characteristics; although a campaign’s initiation may be rapid and intense, its success depends on engaging the audience with disseminated content, particularly during the critical amplification stage, for sustainable online mobilization.

Network analysis further supports this finding, as the overall structural integrity measurements of the anti-disinformation campaign were found to be strong during the amplification stage. Additionally, the high presence of anti-disinformation commenters in both campaigns, particularly during the amplification stage, highlights key mobilization characteristics that may have played a crucial role in countering and diffusing the disinformation narratives. These insights are pivotal for developing effective mobilization strategies to counter disinformation and bolster the resilience of democratic societies against the evolving online challenges.

However, despite providing valuable findings, this study is not without its limitations, which we plan to address in future research. Incorporating user demographics such as age, gender, and political orientation could enhance the identification of targeted audiences. Additionally, assessing the impact of both campaigns on public opinion is crucial for a comprehensive understanding. Addressing these limitations in future work will enable a more nuanced and thorough analysis of the mobilization characteristics of these campaigns.

While this study offers a perspective via socio-computational methods on identifying mobilization aspects of social movement campaigns, our novel multi-method analysis significantly contributes to the growing body of literature that aims to characterize various types of social movements through the lens of mobilization and collective action.

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