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Unveiling the waves of mis- and disinformation from social media

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In the digital era, social media platforms have become the focal point for public discourse, with a significant impact on shaping societal narratives. However, they are also rife with mis- and disinformation, which can rapidly disseminate and influence public opinion. This paper investigates the propagation of mis- and disinformation on X, a social media platform formerly known as Twitter. We employ a multidimensional analytical approach, integrating sentiment analysis, wavelet analysis, and network analysis to discern the patterns and intensity of misleading information waves. Sentiment analysis elucidates the emotional tone and subjective context within which information is framed. Wavelet analysis reveals the temporal dynamics and persistence of disinformation trends over time. Network analysis maps the intricate web of information flow, identifying key nodes and vectors of virality. The results offer a granular understanding of how false narratives are constructed and sustained within the digital ecosystem. This study contributes to the broader field of digital media literacy by highlighting the urgent need for robust analytical tools to navigate and neutralize the infodemic in the age of social media.

Keywords: Misinformation; disinformation; X (Twitter) data; social media; multidimensional analytics.

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1. Introduction

In the contemporary digital landscape, social media platforms not only facilitate global connectivity but also play a critical role in the construction and dissemination of information. X, formerly known as Twitter, stands as a testament to this phenomenon, acting as a virtual town square where ideas flourish and news travels at unprecedented speed. Yet, this rapid information exchange comes with the pernicious side-effect of mis- and disinformation, phenomena that undermine information integrity and skew public perception. Mis- and disinformation are not new phenomena themselves, as many researchers were concerned about them and published their findings (see, for instance, Refs. 1, 2, or 3). However, the development of social media has fueled the dissemination of mis- and disinformation more than correct and reliable information.[4]

Mis- and disinformation represent a significant challenge in the age of digital media. Misinformation, often stemming from erroneous understandings or the accidental spread of falsehoods,[5] and disinformation, which is the deliberate creation and dissemination of false narratives,[5] both have the potential to escalate into social, political, and health-related crises.[6–8] The implications of these malicious practices are far-reaching, affecting elections,[9–11] public health responses,[7,12,13] and even inciting violence.[14]

The fight against the spread of misinformation comes as a challenge, as it necessitates constant monitoring and detection of misinformation being spread.[6,15–19] As misinformation usually spreads faster than the related debunking information,[4] just detecting the misinformation wouldn't solve the problem. An efficient and effective fight against misinformation needs to estimate the dissemination of misinformation before the wave starts. Otherwise, the corrective information would not reach all the communities affected by the spread of misinformation in time. One reliable way to estimate the misinformation dissemination before it goes viral is to analyze the public conversations and discussions on social media platforms to indicate the community's concerns and provide relevant information to address those concerns.[6,15,20] Tracking public conversations to elicit public concerns not only helps fight against misinformation but can also help policymakers address those concerns, which in turn can help strengthen democratic policymaking and prevent the manifestation of new rumors and disinformation campaigns.

The first step in tracking public conversation on a topic is detecting the conversations and discussions around that topic. As people express their opinions, concerns, and personal experiences on social media platforms, these platforms can serve as valuable tools for identifying and tracking ongoing public conversations and discussions.

Public conversation might not be in the form of direct dialogue. For instance, the public conversation about "democracy" contains all the posts, statements, or expressed opinions on "democracy". Some statements will be responses to other statements without mentioning (or knowing) who made them in the first place. In other words, someone in a discussion might express an opinion that gets accepted or promoted by others; another person, in turn, might criticize the opinion without knowing who initiated it. The expression of opinion and then criticizing that opinion will form a general discussion without each side knowing who on the other side expressed the opinion or criticized the opinion. Furthermore, there is no facilitator or moderator to decide when the discussion should be started and which statement is relevant to the discussion and which one is not. In other words, the public conversation is formed by people's interest in the topic, facilitated by the people, has no clear structure or endpoint, and includes both direct and indirect responses to other participants' statements, opinions, and criticism.[21,22] Although the findings from social media do not represent all communities in society, the results from popular social media platforms can be used to understand the public opinions and concerns of parts of society. Since almost all communities in society interact with each other and have the potential to influence other communities' opinions or concerns, the findings from popular social media platforms still carry valuable insights on public opinions.[23–25]

Conversations in general and on social media platforms in particular can be analyzed based on their structure, their content, and participants' interactions.[26,27] However, as mentioned before, public conversations and discussions include indirect dialogues where participants do not interact directly and might lack a clear structure and endpoint. Analyzing such a conversation should primarily focus on the content of the conversation. Furthermore, analyzing the content of public conversation and discussion can reveal public opinion and public concerns around a topic.[24,28,29]

With the burgeoning influence of social media, understanding the mechanics of mis- and disinformation is crucial. The ephemeral and networked nature of social media platforms like X requires sophisticated tools to track and analyze the spread of information. This study leverages text analysis and network analysis to extract public conversations, sentiment analysis to gauge the emotional responses that such information elicits, and wavelet analysis to examine the temporal patterns.

The primary objective of this research is to propose a method for extracting and tracking public discussions and sub-discussions around a topic from social media platforms. Different indices are formulated to measure and track the popularity of a discussion among social media users. The proposed method and indices are used to extract public discussion around misinformation and democracy from the X platform (former Twitter).

The rest of this paper is organized as follows. Section 2 outlines the methodology, including sentiment analysis, wavelet analysis, and network analysis. Section 3 presents the results and discussions, interpreting the findings within the context of digital communication theory. Finally, Sec. 4 concludes with the implications of the study, limitations, and directions for future research.

2. Methodology

Before diving into analysis, it was imperative to ensure the purity of our data. A meticulous data sanitization phase was thus instigated, which encompassed duplicate removal, spam content elimination, and rectification of any dataset inconsistencies. R — a versatile statistical software — became our tool of choice for data scrutiny, supplemented by a proprietary tool we developed for a bird's-eye view of the collated data.

Transitioning to the preparatory phase for analysis, our data were sculpted and refined. This involved textual data undergoing normalization, tokenization, stemming, and the purge of stop words. Beyond this, depending on our research objectives, we also segmented, aggregated, and filtered the data, pinpointing specific time-frames or data subsets.

In sum, our methodological journey — spanning from data procurement to analysis — embodied a blend of comprehensive data strategies. It was this very blend that unlocked profound insights into the digital narrative surrounding floods and earthquakes, enriching our comprehension of user dynamics and inclinations in this sphere.

2.1. *Text mining and sentiment analysis*

Text mining and text analysis models are powerful tools to analyze social media content, as most of users' expressed opinions and discussions on social media platforms are in textual format.[30]

The first step in analyzing textual data is to represent blocks of text, usually referred to as documents in such a format that they can be analyzed by mathematical algorithms.[30] This representation can be based on preexisting word libraries, the structure of the documents, the structure of sentences, or a combination of those aspects.[31] One initial step is detecting and removing the stopping words (words like "the", "are", etc.) as building the bag-of-words to highlight the more important content of the document.[30]

Using detecting entity models[32–34] and key phrase extracting models,[35] gives a better image of important content in each document. In addition to recognizing the important contents of the documents, sometimes, it is imperative to get the sentiment of each document as well. Fusing the sentiment with the structural content of the documents gives details on the opinion presented in the document. This would be very crucial for opinion mining.[30]

Sentiment models are either calculating a sentiment score or sentiment probability to assign the document to one of the sentiment classes "positive", "neutral", or "negative".[36] For more details on the mathematical formulation of sentiment analysis, see Ref. 37. For practical applications, there are a number of advanced packages developed for sentiment analysis based on deep learning algorithms that take into account the sentiment of words in the bag-of-words as well as the structure of the sentences in the document.[38–41]

2.2. *Network analysis*

Another useful tool adopted for social media text mining is network analysis (see Refs. 42–46 for different approaches). Network analysis, in general, studies the structure of interconnectivity in a given network. As many complex systems can be represented as a network, such analysis sheds light on the mechanics of such systems and reveals the potential vulnerability in the network.[47]

In social media analysis, networks can be used to represent the user's connectivity and the structure of their reactions to each other's posts.[44–46] In text mining, on the other hand, network analysis can be used for analyzing the linkage between different parts of a text.[42,43] A combination of these two approaches reveals the structure of direct conversations among social media users.[48–50] In the network representation of a system, each component is shown as a node, and each link between the system's components is shown as an edge. In this manner, the system can be analyzed through the paths in its network, the distance between different nodes, the connectivity of the system, and other characteristics of the network. Furthermore, applying cluster analysis to the network can reveal sub-systems in the system.[51] In the cluster analysis of a network, either nodes or edges get clustered based on their characteristics. Each cluster of network components and edges is named a community. For instance, the community linkage method[51,52] builds sub-communities by clustering the network edges. If the edges are clustered, each component of the system (nodes in the network) might belong to multiple clusters. For mathematical details on network representation of a complex system and network analysis, see Ref. 47.

2.3. *Wavelet analysis*

To get a better understanding of any social phenomenon, it is imperative to track and analyze that phenomenon over time. Like many social phenomena,[53,54] people's behavior on social media platforms and their interest in different topics have stochastic and periodic patterns.[55,56] Among the methods developed to extract such patterns, wavelet analysis is popular, as it is nonparametric and can account for changes in periodic behavior over time. Authors in Refs. 55 and 56 employed the wavelet method to effectively investigate cyclical patterns in different social variables and their links over time.

A continuous wavelet transform (CWT) uses a continuous base function to decompose a time series with complex periodic patterns into several time series with single periodic patterns. The wavelet transform has generalized classic frequency domain analysis by using a more flexible base function instead of the classic choices of sine and cosine functions. Such a base function is the wavelet transform formulation, which is usually referred to as the mother wavelet. Suppose $\{y_t\}_1^n$, is a discrete-time time series. CWT uses the mother wavelet $\psi(\cdot)$ to transform $\{y_t\}_1^n$ with the time localization parameter τ and the scale parameter s with the following equations:

$$W_\psi\{y\}(\tau, s) = \sum_{t=1}^{n} y_t \frac{1}{\sqrt{s}} \overline{\psi}\left(\frac{t-\tau}{s}\right),$$

where $\overline{\psi}(\cdot)$ denotes the complex conjugate of the mother wavelet. $\psi(\cdot)$. The scale parameter s denotes localized wavelength. Large values of s indicate periodic behavior with a long period length (small frequency). Parameter τ illustrates the localized time in which the periodic behavior has happened. One very common choice of mother wavelet function is the Morlet wavelet.[57] The reason the wavelet has become popular is that under milled conditions (for certain parametrizations), it becomes approximately analytic.[58]

Since the large absolute values of the wavelet coefficient $W_\psi\{y\}(\tau, s)$ indicate powerful periodic behavior, it can be used to construct the wavelet power spectrum surface:

$$\text{Power}_\psi\{y\}(\tau, s) = \frac{1}{s}|W_\psi\{y\}(\tau, s)|^2.$$

$\text{Power}_\psi\{y\}$ is a useful tool in investigating periodic patterns in social time series.[55,56] However, since it is an estimation of the actual power spectrum, it is important to test for its significance before using it to determine cyclical patterns. The significance of the wavelet power spectrum can be tested either with the asymptotic chi-square statistic[59] or Monte Carlo simulation[60] ; the latter method is used in this research.

2.4. *Network representation of key phrases*

In general, a text can be reduced to its key phrases to extract the main message and content from a text. Once key phrases from different texts are available, they can be used to investigate similarity or connections amongst a set of texts. As key phrases represent key concept of a text, each post on social media can be reduced to its key phrases. In other words, set of key phrases in each post can be used to express the main topic of that post. Table 1 shows an example of key phrases extracted from a tweet using Microsoft Azure Text Analyzer.

In social media, even though not all posts are replies to specific posts or targeted specific user, all the posts related to a subject, eighter express users'

Table 1. Illustration of key phrases extracted from a tweet.

Tweet's text	Extracted key phrases
"Ireland was long considered an exception to Europe's drift to the right. But with a housing crisis & anti-immigration protests fuelling far-right activity, this no longer seems to be the case. Aoife Gallagher features in the @nytimes talking about it. https://t.co/BK2B2JSYVs"	Housing crisis, anti-immigration protests, far-right activity, Aoife Gallagher, Ireland, exception, Europe, drift, case, BK2B2JSYVs

perception/concerns/statements on the subject or addresses the perception/concerns/statement of a group of a people. In this regard, a set of posts in social media can be considered as a discussion amongst a group of people, even though not all posts are direct replies to other users.

Connections and relations between concepts in said discussion can be demonstrated and analyzed using a network of key phrases. In the network of key phrases, each node represents one key phrase. Two nodes have an edge (without direction) between them if their respected key phrases are appeared in one post. The size of the nodes is proportional to the frequency of its key phrase, in whole discussion and the thickness of an edge is proportional to the frequency of two key phrases appear in the same post throughout the discussion. Defining such key phrase network as explained illustrates the connectivity between different key phrases in the discussion.

2.5. *Clustering networks and sub-discussion extraction*

In each discussion, people might approach the subject from different angles. Each approach or focus to the discussion is a sub-discussion. For instance, in discussion about misinformation, one might approach the subject from its effect on people's health whilst others might focus on the incidence related to politics.

One approach to extract sub-discussions is to apply network clustering methods to key phrase network. As each cluster represents the subnetwork (usually called community) with similar nodes or edges, the communities in key phrase network can be interpreted as key phrases from sub-discussions.

There are a variety of network clustering methods developed. In this research, the community linkage[51,52] is used to cluster the key phrase network.

2.6. *Discussion popularity index*

Whilst key phrase network and network clustering methods can be used to illustrate and analyze the discussion on a subject in social media, they are unable to track the changes in discussion over the time. Following indices makes it possible to track and analyze evolution of discussion and its sub-discussions over the time.

2.6.1. *Discussion popularity index*

Let's define the Discussion Popularity Index (DPI) of a discussion as the standardized number of posts related to its key phrase network. From the definition of key phrase network given above, a post is related a key phrase network if it contains at least one pair of adjacent key phrases from network (key phrases which are directly connected in the network). In other words, if keywords "A" and "B" are adjacent in the specific key phrase network (there is a "A–B" edge in the key phrase network), all posts with both key phrases "A" and "B" are related to that key phrase network. Using the above definition, DPI at time t is formulated as follows:

$$\begin{aligned}
\mathrm{DPI}_t &= \frac{\mathrm{DTP}_t}{\max_t\left(\mathrm{DTP}_t\right)} \times 100, \quad t = 1, \ldots, T, \\
\mathrm{DTP}_t &= \sum_{i=1}^{n_t} U(p_{i,t}), \quad t = 1, \ldots, T, \\
U(p_{i,t}) &= \begin{cases} 1 & \text{if } p_{i,t} \text{ contains at least one edge of key phrase network}, \\ 0 & \text{otherwise}, \end{cases} \\
p_{i,t} &\in B_t,
\end{aligned}$$

where DPI_t is the DPI for the given discussion at time t, DTP_t is the discussion total posts at time t, B_t is the batch of posts to be analyzed (pulled from social media) which are posted on social media at time t, $p_{i,t}$ is the ith post in B_t and n_t is the number of posts in B_t.

In case there are more than one discussion (more than one key phrase network), e.g., when there are multiple sub-discussions, the DPI can be formulated as follows:

$$\begin{aligned}
\mathrm{DPI}_{t,k} &= \frac{\mathrm{DTP}_{t,k}}{\max_{t,k}\left(\mathrm{DTP}_{t,k}\right)} \times 100, \quad t = 1, \ldots, T, \\
\mathrm{DTP}_{t,k} &= \sum_{i=1}^{n_t} U_k(p_{i,t}), \quad t = 1, \ldots, T, \\
U_k(p_{i,t}) &= \begin{cases} 1 & \text{if } p_{i,t} \text{ contains at least one edge of } k\text{th key phrase network}, \\ 0 & \text{otherwise}, \end{cases} \\
p_{i,t} &\in B_t,
\end{aligned}$$

where $\mathrm{DPI}_{t,k}$ is the DPI for discussion k at time t, $\mathrm{DTP}_{t,k}$ is the discussion total posts at time t for kth sub-discussion, B_t is the batch of posts to be analyzed (pulled from social media) which are posted on social media at time t, $p_{i,t}$ is the ith post in B_t and n_t is the number of posts in B_t. With the above definition, the discussion (or sub-discussion) with higher DPI at time t has the higher popularity (i.e., the higher number of posts have been related to that discussion) at time t.

2.6.2. *Adjustment for the level of relevance*

DPI, as defined above, relies on the number of posts related a discussion, regardless how much each post is related to the discussion. In other words, the post which only includes one edge of the key phrase network has the same impression in DPI as the post which includes all the edges (all the key phrases from key phrase network). This issue can be addressed with Discussion Involvement Index (DII), which measures the relevance of one social media post to a given discussion (key phrase network) based on edges included in the post. DII formulates as follows:

$$\mathrm{DII}_{i,k} = \frac{N_{i,k}}{\sum_i (N_{i,k})},$$

$$N_{i,k} = \sum_{j=1}^{h_k} I((v_1, v_2)_{k,j} \in p_i),$$

$$I((v_1, v_2)_{k,j} \in p_i) = \begin{cases} 1 & \text{if both key phrases } v_1 \text{ and } v_2 \text{ are mentioned in } p_i, \\ 0 & \text{otherwise,} \end{cases}$$

$$B = \bigcup_{t=1}^{T} B_t,$$

where B is the batch of all available posts, $DII_{i,k}$ is the DII for ith post in batch B related to kth discussion/sub-discussion (kth key phrase network), $N_{i,k}$ is the number of edges from kth key phrase network mentioned in ith post, p_i is the ith post of batch B, $(v_1, v_2)_{k,j}$ is the jth edge of kth key phrase network and v_1 and v_2 two ends of edge $(v_1, v_2)_{k,j}$. Higher values of $\mathrm{DII}_{i,k}$ indicate that the ith post, from pulled batch of social media posts, is more relevant to (more involved in) discussion presented as key phrase network k.

Employing DII can incorporate relevance of posts to a topic, when calculating DPI, adjusting the index for relevance of the post. The adjusted DPI formulates as follows:

$$\mathrm{DPI}_{\mathrm{adj}_{t,k}} = \frac{\mathrm{WDTP}_{t,k}}{\max_{t,k}(\mathrm{WDTP}_{t,k})} \times 100, \quad t = 1, \ldots, T,$$

$$\mathrm{WDTP}_{t,k} = \sum_{i=1}^{n_t} \mathrm{DII}_{i,k} U_k(p_{it}), \quad t = 1, \ldots, T,$$

$$U_k(p_{i,t}) = \begin{cases} 1 & \text{if } p_{i,t} \text{ contains at least one edge of } k\text{th key phrase network}, \\ 0 & \text{otherwise,} \end{cases}$$

$$p_{i,t} \in B_t,$$

where $\mathrm{DPI}_{\mathrm{adj}_{t,k}}$ is the adjusted DPI for discussion k at time t, $\mathrm{WDTP}_{t,k}$ is the weighted discussion total posts at time t for kth sub-discussion, B_t is the batch of posts to be analyzed (pulled from social media) which are posted on social media at time t, $p_{i,t}$ is the ith post in B_t and n_t is the number of posts in B_t.

3. Results

The dataset used in this research contains 9850 tweets with the keywords "Misinformation" or "Disinformation" and at least one of the following keywords: "Election", "Democracy", "Justice", "Government", "Freedom", "Liberal", "Liberty", "Human", "Democrat", "Republican", "Republic", "Nation", "Society", "Citizen", "Parliament", "Right", "Justice", "Dictator", "Trump", "Biden", "President", "Conservative", "Conspiracy", "Nationalist", "Nationalism". The pulled tweets are posted on X between "18:00:00 UTC, January 5th, 2024" and "18:00:00 UTC, January 9th, 2024". The retweets of the same tweet are excluded to avoid inflation on the same exact content and to include more tweets. The time interval includes 6 January and 8 January, which mark the attacks against Congress (in the US and Brazil) in protest of the US and Brazilian elections in 2021 and 2023, respectively. It is also before the European Parliament's vote on the "EU Artificial Intelligence Act". Around this period, there had been coverage in the news outlets about the potential impact of AI on the spread of misinformation and elections (for instance, see Refs. 61–68).

The tweets were pulled from the X platform using API requests with the following query main parameters:

```
'query' = "((Misinformation OR Disinformation) AND
           (Election OR Democracy OR Justice OR Government OR
             Freedom OR Liberal OR Liberty OR Human OR Democrat OR
             Republican OR Republic OR Nation OR Society OR Citizen
             OR Parliament OR Right OR Justice OR Dictator OR
             Trump OR Biden OR President OR Conservative OR
             Conspiracy OR Nationalis)) -is:retweet",
'start_time' = "2024-1-5T17:30:00-00:00",
'end_time' = "2024-1-9T17:30:00-00:00".
```

Figure 1 shows the conceptual model used for detecting and analyzing public discussion and expressed opinions and perceptions around above-mentioned keywords, structure of sub-discussions and the cyclical patterns and linkage over time.

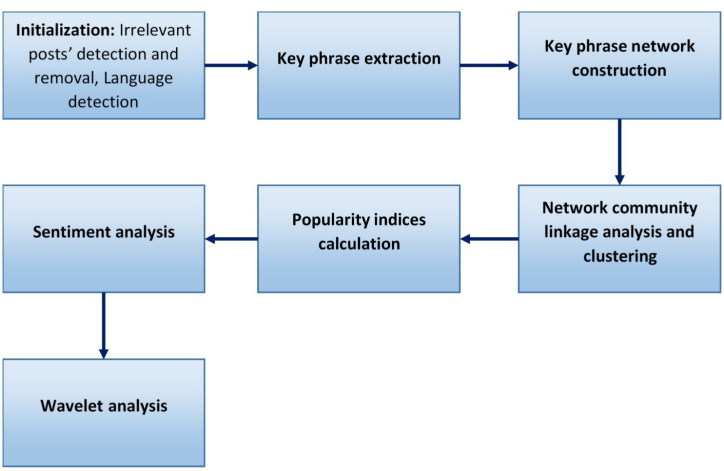


Fig. 1. Conceptual model used for detecting and analyzing public discussion.

3.1. *Key phrase network analysis*

As proposed in Sec. 2, key phrases from pulled tweets are used to build the content network. The key phrases are extracted by the "Microsoft Azure Text Analyzer" toolbox.[38] After extracting the key phrases, the network of these phrases is constructed. This network is then utilized to analyze the content structure of the pulled tweets as public discussion. The basic rules for constructing the key phrase network are as follows:

- Each node in the network represents one of the key phrases.
- Each edge connects a pair of key phrases that appeared in the same tweet.
- The nodes' size is proportional to the frequency of the corresponding key phrase being used in all tweets.
- The thickness of the edge between two nodes is proportional to the frequency of two key phrases appearing in the same tweet among all tweets.

The key phrase network for the 600 most frequent key phrase pairs is shown in Fig. 2. As it can be seen, most of the frequent key phrases are related to the US political disputes and the presidential election. Furthermore, there are other key phrases related to vaccines, health, and climate. Figure 2 also shows that there are signs of clusters in connected key phrases. For instance, "Climate", "Vaccine Misinformation", "Universal Figure", and "Cranky Uncle"[a] form an isolated cluster of key phrases, while "Fake Images", "AI-Generated Image",[b] "Disinformation", and some other key phrases from another cluster that are connected to each other (either directly or through the "Disinformation" node), but not directly connected

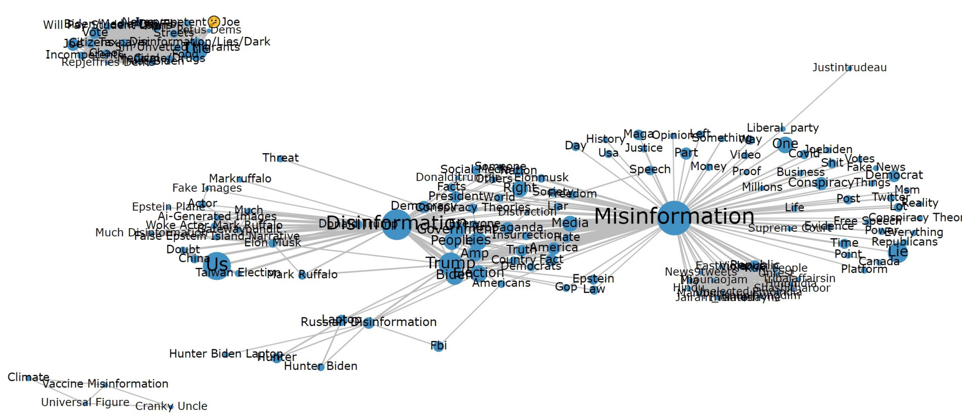


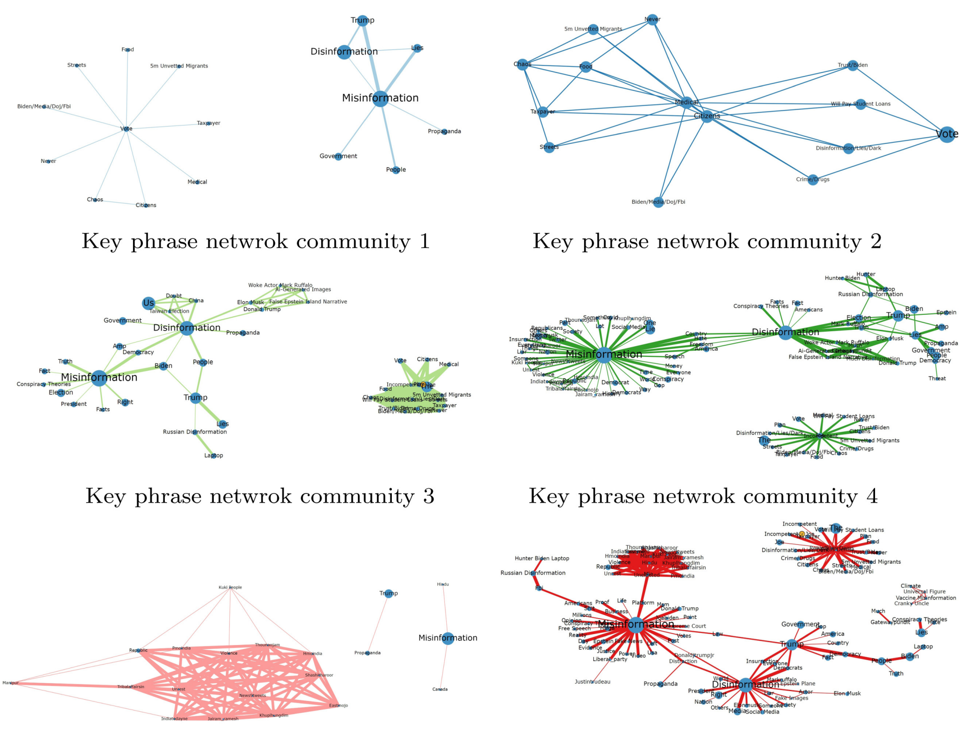
Fig. 2. Key phrase network extracted from pulled tweets.

[a]Cranky Uncle is a mobile game app that uses cartoons and critical thinking to fight misinformation (see crankyuncle.com for more details).
[b]Some key phrases in this cluster refer to an incident in which Mark Ruffalo quote-tweeted a tweet containing an AI-generated image. He posted the next day with an apology and clarification.[69]

to the rest of the key phrases; neither are completely isolated. This structure of connections between key phrases suggests there might be sub-discussions formed around the above-mentioned key phrases.

In order to extract sub-discussions based on the structure of key phrase connections, the community linkage method[51,52] is used to extract network clusters of related key phrases. Each linked community (network cluster) of key phrases can be used as a representation of key phrases in a sub-discussion amongst X users. In other words, clustering the network of key phrases can reveal different public sub-discussions on social media.

Extracted subnetworks are presented in Fig. 3. As it can be seen, the first community's key phrases are mostly related to general concerns about mis- and disinformation, governments, and social issues like lies, citizens, taxes, and migration. The key phrases in the second cluster are more related to concerns about elections in general, without including mis- and disinformation key phrases, although all key phrases have a general connection to mis- or disinformation. The third community's key phrases are more related to specific incidents or claims related to the US presidential election, as it still includes the more general key phrases. The fourth



Key phrase netwrok community 1

Key phrase netwrok community 2

Key phrase netwrok community 3

Key phrase netwrok community 4

Key phrase netwrok community 5

Key phrase netwrok community 6

Fig. 3. Key phrase network extracted from pulled tweets.

and sixth clusters include more key phrases as they are the largest ones. The fourth cluster contains mostly key phrases related to policies, election and conspiracy theories, political claims, and incidents, while the sixth community involves the same key phrases (with different structural connections) and more general key phrases related to climate, health, and figures from Canada and India. The fifth cluster includes mostly key phrases related to concerns around mis- and disinformation in India and Canada.

3.2. *Content summarization*

Summarizing the content of related tweets can help to get a better understanding of public discussion and sub-discussions. The summary of sub-discussions (related to each community of key phrases) is extracted using ChatGPT 3.5. Tables 2 and 3 show the summary of discussions extracted from key phrase communities.

Table 2. Summary of sub-discussions and their topics for each community of key phrase networks 1, 2, and 3.

Community	Topic	Summary
1	The topic of the following text is accusations and allegations of misinformation spread by various individuals and entities, including the US government, western governments, media, and politicians.	The discussion revolves around accusations and allegations of misinformation spread by various entities such as the US government, western governments, medical regulators, mainstream media, and politicians. It covers topics like disinformation, Trump, the media, political events, immigration, and COVID-19. The discussion highlights the division and differing perspectives on these issues. Additionally, it discusses accusations against Mark Ruffalo for sharing fake images of Trump on Epstein's plane and Elon Musk for allowing disinformation on his platform. Some users defend Ruffalo, while others criticize him. Russian involvement, Hunter Biden's laptop, and COVID-19 disinformation are also mentioned in the discussion.
2	The main topic of the following text is the discussion on Twitter about the Democratic Party's alleged plan for 2024 and concerns related to taxpayer expenses, migrants, medical costs, and the spread of medical misinformation.	The discussion on Twitter is about the Democratic Party's alleged plan for 2024, accusing Biden, the media, DOJ, and FBI of using disinformation to deceive voters. Concerns are raised about taxpayer expenses for student loans, migrants, food, and medical costs, as well as chaos, unvetted migrants, crime, and drugs. A tweet criticizes the spread of medical misinformation and its potential consequences.

Table 2. (*Continued*)

Community	Topic	Summary
3	The main topic of the following text is the prevalence of misinformation in politics and its impact on public opinion and elections.	The discussion revolves around the prevalence of misinformation in politics, with users discussing various incidents and accusing different groups of spreading false information. There are mentions of specific political figures, such as Trump and Hunter Biden, and discussions about the role of the media and the impact of misinformation on public opinion and elections. The discussion also touches on topics like platform regulation, media responsibility, and the need to protect free speech while combating disinformation.

These results show that employing a LLM (ChatGPT 3.5 in this case) in combination with key phrase network analysis can effectively extract the different discussions on social media. Once the content of public discussion and sub-discussions is summarized, one can track the shifts in people's interest in each sub-discussion by analyzing its popularity over time.

Table 3. Summary of sub-discussions and their topics for each community of key phrase networks 4, 5, and 6.

Community	Topic	Summary
4	The main topic of the following text is political controversies and discussions surrounding various issues, including the Hunter Biden laptop story, allegations of Russian disinformation, Trump's actions on insulin prices, Biden's involvement in healthcare, and criticisms of politicians from both sides.	The discussion revolves around various political controversies, including the Hunter Biden laptop story and allegations of Russian disinformation. Users express differing opinions on the media's handling of the laptop story and discuss other political issues such as Trump's actions on insulin prices and Biden's involvement in healthcare. Criticisms of politicians from both sides are also mentioned.
5	The main topic of the following text is the discussion on Twitter regarding allegations of propaganda and misinformation, involving Trump and his supporters, the Capitol riot, COVID-19, and foreign actors' role in spreading propaganda.	The discussion on Twitter revolves around allegations of propaganda and misinformation, with some users accusing Trump and his supporters of spreading lies and others defending him. The discussion also touches on topics such as the Capitol riot, COVID-19, and foreign actors' role in spreading propaganda. There are differing opinions and accusations throughout the discussion.

Table 3. (*Continued*)

Community	Topic	Summary
6	The main topic of the following text is the discussion on Twitter regarding allegations and counter-accusations of misinformation and conspiracy theories.	The discussion on Twitter revolves around allegations and counter-accusations of misinformation and conspiracy theories. Users discuss the involvement of political figures in spreading false information and express concerns about its impact on society. Some users defend themselves against accusations while others call for fact-checking and the removal of misinformation.

3.3. *Popularity indices time series*

Using the DPI and $\mathrm{DPI}_{\mathrm{adj}}$ as measures of popularity for each sub-discussion, the popularity of each combination of key phrases on X can be tracked over time. Figure 4 shows the hourly DPI and $\mathrm{DPI}_{\mathrm{adj}}$ for these six communities of key phrases, extracted and summarized earlier, over time. According to DPI (top panel in Fig. 4) the number of tweets in most sub-discussions has strong and obvious periodic behavior, except for sub-discussions 2 and 5. Furthermore, there has been a sudden increase in the popularity of most sub-discussions (all communities except community 5) at "23:00, January 8th, 2024", with the highest number of tweets related to sub-discussion 4. It also shows that sub-discussion 2 only got popular in that time period, which suggests that the spike was due to the formation of sub-discussion 2 and has vanished after that sub-discussion lost its popularity. The sudden formation of a sub-discussion and sudden loss of its popularity can be caused by an unforeseen event (which should show its effect on other social time series like the news trend) or it might be caused by a planned advertisement campaign.

Once the DPI is adjusted based on the relevance of the tweets (see DPI.adj in Fig. 4), the highest popularity over time belongs to sub-discussion 2. In other words, the sudden spike in people's involvement in these sub-discussions (at "23:00, January 8th, 2024") is due to their tweets on sub-discussion 2 (which has shared key phrases with other sub-discussions). Furthermore, according to $\mathrm{DPI}_{\mathrm{adj}}$ (shown in the bottom panel of Fig. 4), there is another sudden increase in people's involvement in sub-discussion 5 at "10:00, January 9th, 2024", which, according to DPI, does not include a large number of tweets but a large number of very relevant tweets (according to $\mathrm{DPI}_{\mathrm{adj}}$).

3.4. *Sentiment time series*

Incorporating these methods with sentiment analysis will reveal more details on these sub-discussions. Figures 5 and 6 show the sentiment decomposition of DPI and $\mathrm{DPI}_{\mathrm{adj}}$.

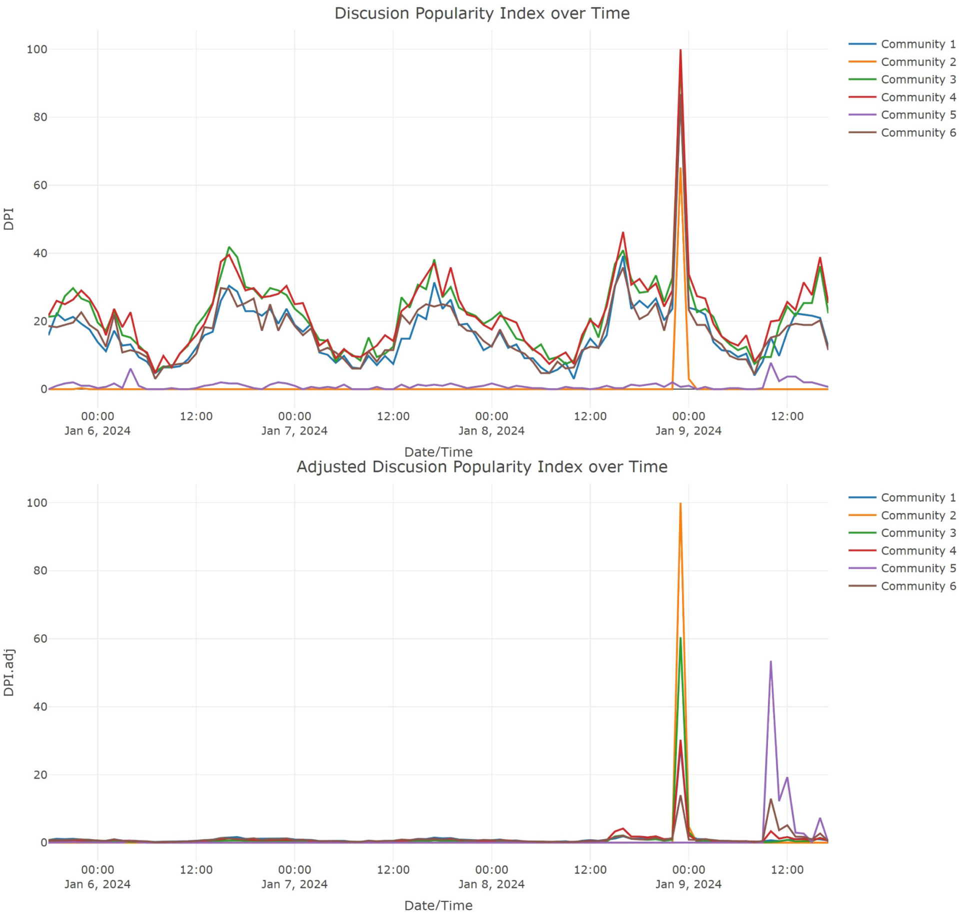


Fig. 4. DPI and its adjustment for sub-discussions 1–6 (key phrase network communities 1–6) over time.

The sentiment of the tweets is estimated using the Microsoft Azure library. As it can be seen, in all sub-discussions, over time, the majority of the tweets have negative sentiment, except for a very brief time in sub-discussion 4, at "15:00 and 20:00, January 8th, 2024", and in sub-discussion 5, at "20:00, January 8th, 2024", where the most relevant tweets to these two sub-discussions have neutral sentiment.

3.5. *Waves of discussion popularity*

Decomposing the popularity indices reveals the periodic behavior of people's engagement in public discussion. As mentioned before, the wavelet transform can be used to extract and track significant periodic patterns of any phenomenon over time. The wavelet power spectrum, along with scaled DPI and DPI.adj time series, is shown in Figs. 7 and 8. The estimated wavelet powers are based on CWT

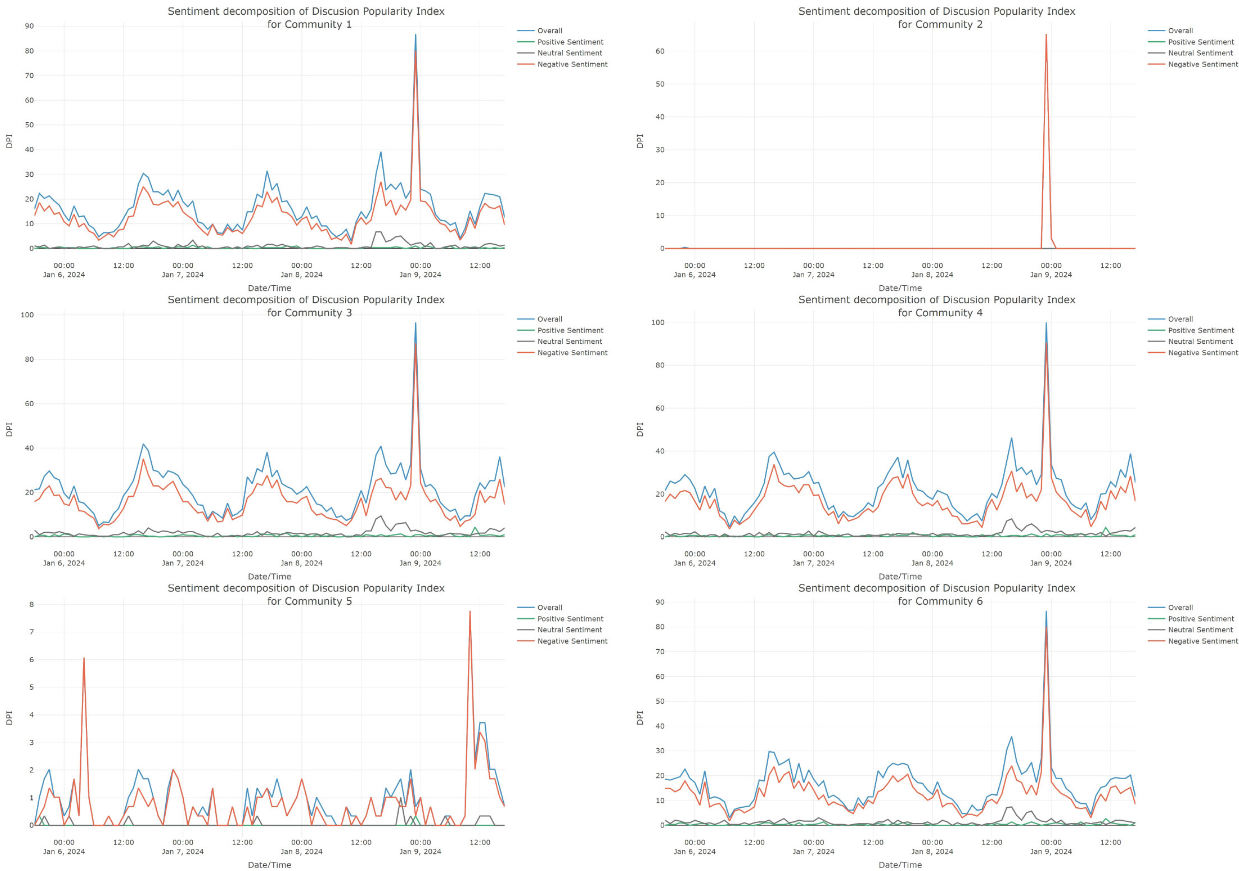


Fig. 5. Sentiment decomposition of DPI for sub-discussions 1–6 (key phrase network communities 1–6) over time.

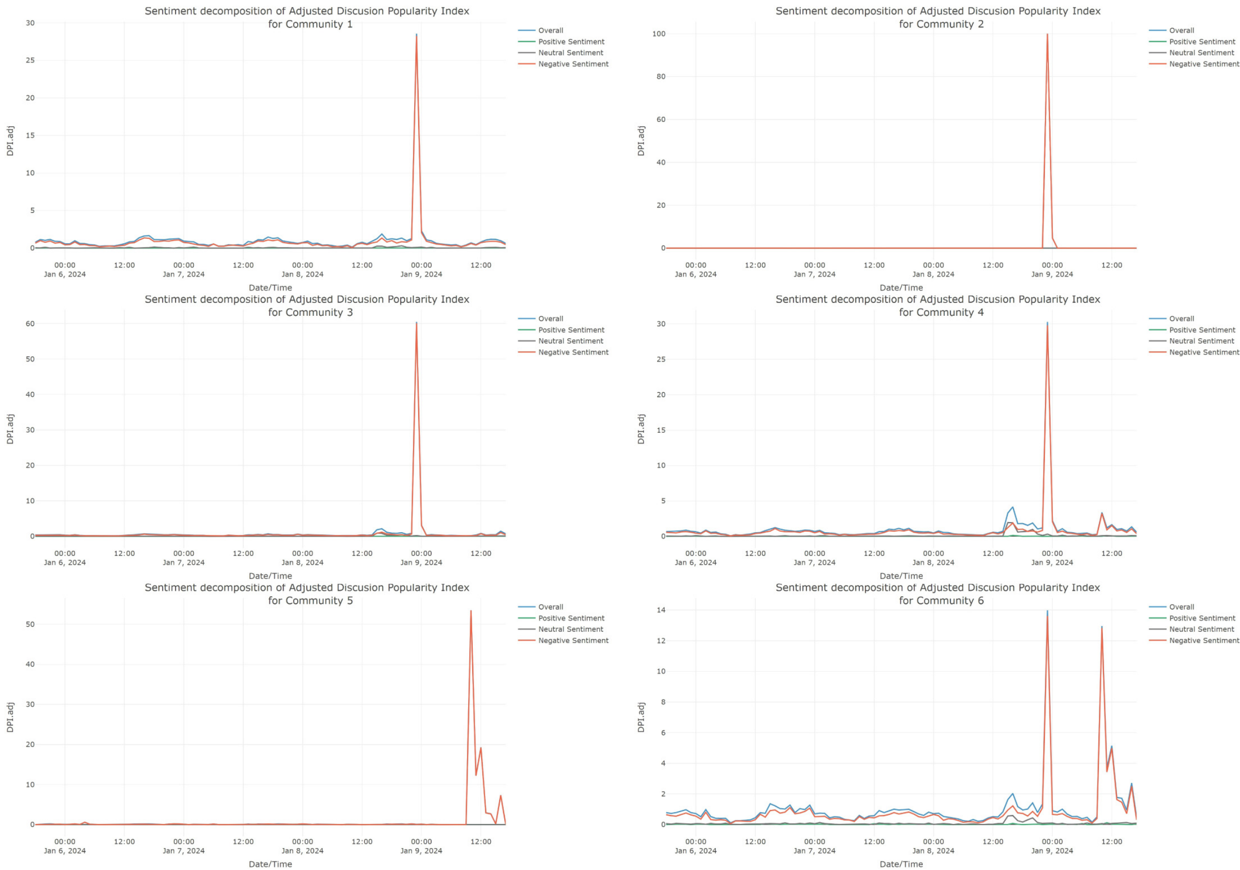


Fig. 6. Sentiment decomposition of adjusted DPI for sub-discussions 1–6 (key phrase network communities 1–6) over time.

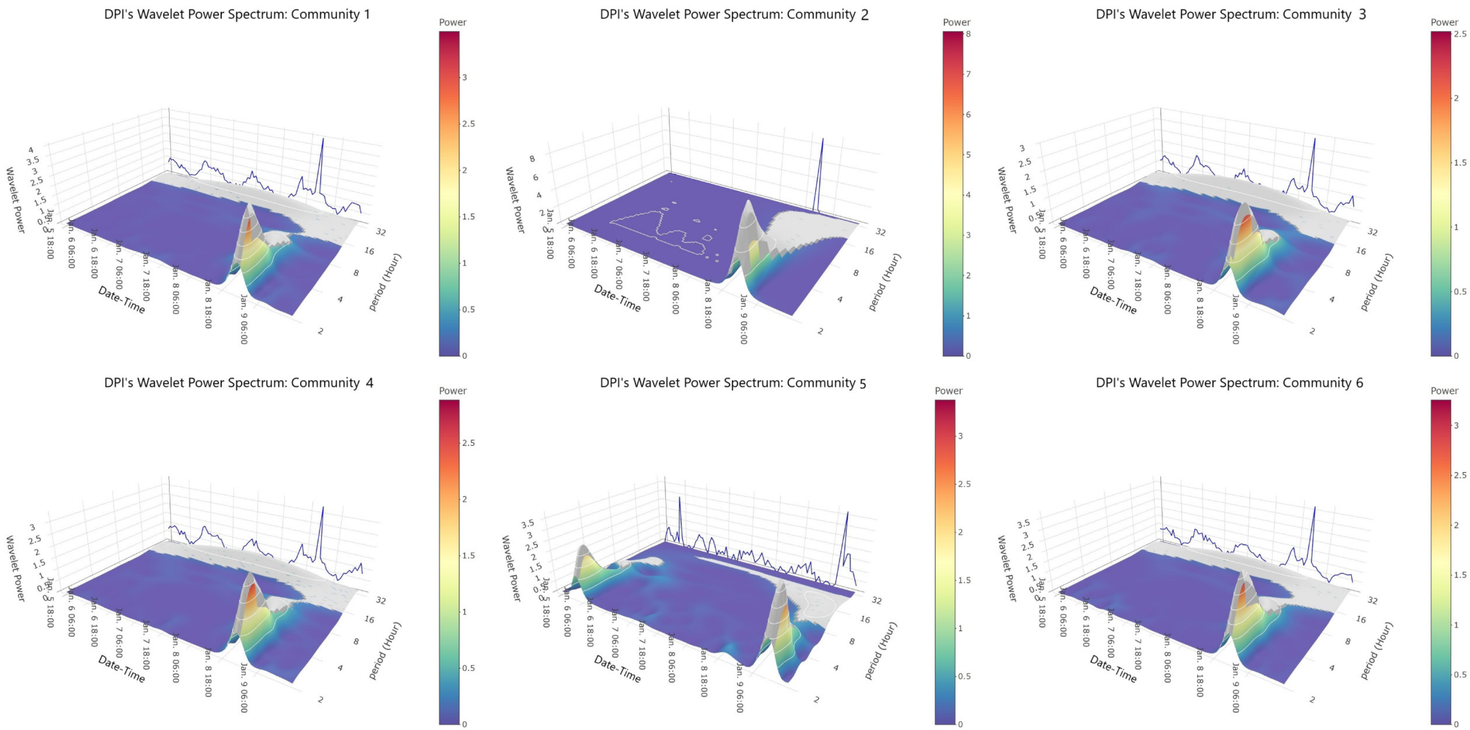


Fig. 7. DPI wavelet power spectrum and their scaled time series for six sub-discussions extracted and summarized earlier. The light gray area shows the significant power spectrum at $\alpha = 0.1$ significance level.

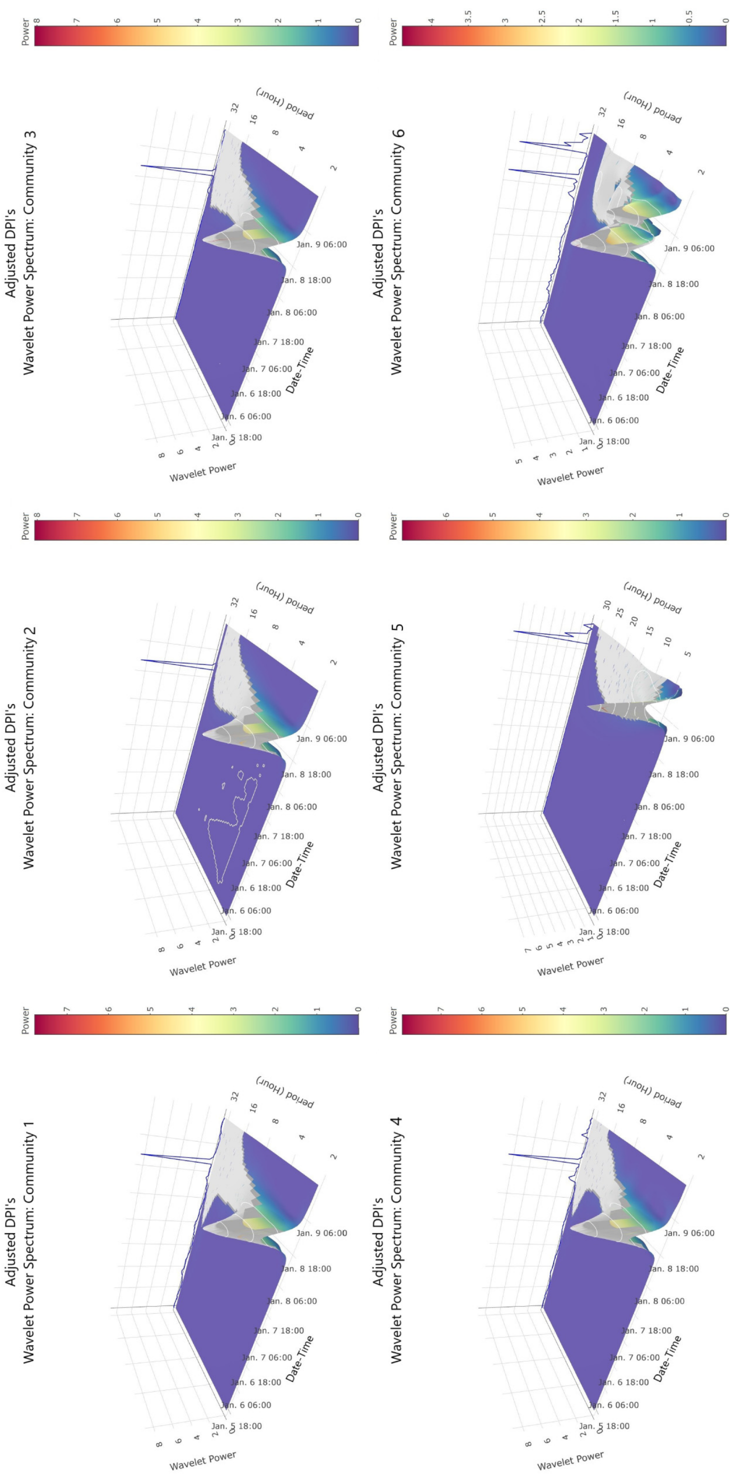


Fig. 8. Adjusted DPI wavelet power spectrum and their scaled time series for six sub-discussions extracted and summarized earlier. The light gray area shows the significant power spectrum at $\alpha = 0.1$ significance level.

with Morlet mother wavelet. The significance of wavelet power is tested at the $\alpha = 0.1$ level of significance using Monte Carlo simulations with 10,000 simulated sample paths. The significant wavelet power is highlighted with a light gray color.

As it is evident in Fig. 7, the periodic behavior of sub-discussions 1, 3, 4, and 6 is very similar. They all have low frequency (long period length), with a period length of around 32 h. In other words, there is a powerful periodic behavior in the popularity of these sub-discussions, in which each period lasts for around 32 h. This periodic pattern exists during the time interval in which data have been collected (i.e., between 18:00, 5 January and 18:00, 9 January). This periodic pattern can partly be related to people's periodic behavior during the 24 h of a day (going to work, getting sleep, etc.). However, the longer period could be in response to other factors, like news programs with specific topics or advertisements or political campaigns responding to each other. According to Fig. 7, sub-discussion 2 mostly has short periodic behavior with very short duration in 8 January. The popularity of sub-discussion 5 also shows short periodic patterns with short duration on 5 January and 9 January. These powerful and short periodic patterns are formed by sudden spikes in the popularity of sub-discussions 2 and 5. The periodic behaviors vanished as popularity fainted. The powerful and short periods in sub-discussions 1, 3, 4, and 6 coincide with the spike in popularity of sub-discussion 2, which shows the high number of shared tweets between these sub-discussions. In other words, the spike in popularity of sub-discussion 2 has affected the number of tweets in sub-discussions 1, 3, 4, and 6, as they share some key phrases.

Since the DPI does not distinguish between tweets that are very relevant to a sub-discussion and more general tweets, it doesn't show if the periodic behavior is due to people's engagement in a specific sub-discussion or not. The popularity of six sub-discussions is shown in Fig. 8.

As Fig. 8 shows, once the popularity is adjusted for relevance of tweets, the significant long-term periodic patterns are removed from sub-discussions 1, 3, 4, and 6. According to these results, the long-term periodic behavior was mostly due to general tweets related to these three sub-discussions. These are tweets that engage in many sub-discussions and topics. Sub-discussions 1, 3, 4, and 6 share a short-term powerful pattern with sub-discussion 2, when relevance is accounted for in the popularity index. In other words, the sudden spike in popularity of sub-discussion 2 has coincided with an increased number of tweets relevant to sub-discussions 1, 3, 4, and 6. Sub-discussion 6, however, has another spike that coincides with the spike in the number of tweets relevant to sub-discussion 5. According to these results, once the popularity of different sub-discussions is accounted for by the relevance of tweets (general tweets are removed), the data show two different spikes in people's interest in public discussion about democracy and mis- and disinformation, on 8 January and 9 January. These increases in interest appeared very sudden and vanished quickly.

4. Conclusion

Understanding and tracking public conversation are some of the cornerstones of detecting and tracking mis- and disinformation dissemination. However, public conversations and discussions have characteristics that make detecting and tracking their content and popularity challenging. For instance, public conversations lack the classic structure of conversation among a group of people. Tracking public conversation and discussion on a social media platform can pose further challenges as the public conversation might get shaped out of the social media platform (e.g., through people's connections in their real-life communities) and then start spreading on the social media platform. In this paper, a method for extracting and analyzing the structure of public discussion content around a topic, along with methods for measuring and tracking the popularity of the public discussion and people's engagement in the discussion, is proposed. The proposed procedure is used to detect and analyze public discussion around democracy and mis- and disinformation, among X platform users.

The results show that the detected discussion around democracy and mis- and disinformation among X platform users includes concerns about mis- and disinformation, government policies, social and health issues, AI-generated misinformation, and elections. According to these findings, the general discussion can be decomposed into six sub-discussions, some concerned with general issues of mis- and disinformation and others focused on more specific incidents and claims. Most of the public discussion about mis- and disinformation and democracy is related to the United States, India, and Canada, which suggests higher participation of users from these countries in the discussion. Analyzing the popularity of sub-discussion shows that there exists a long-term periodic behavior among tweets with general relevance to these topics (rather than relevance to specific sub-discussion). Tweets with a higher level of relevance to the sub-discussions have short term, powerful periodic patterns with very short duration, which are caused by a sudden spike in people's engagement in posting such tweets. Two significant surges of powerful short-term patterns are evident on 8 January and 9 January.

Using the method proposed in this paper, public discussion can be detected and analyzed over time. This opens two new avenues to better understand public concerns, discussions, and perceptions. On the one hand, extracting the structure of public discussion makes it possible to further analyze the structure and content of discussion (e.g., relations between claims, criticisms, and official narratives). However, analyzing the structure of the discussion must be carried out carefully to avoid harming public trust in freely expressing opinions. For instance, focusing on the user's network (for users involved in a public discussion) might give a sense of insecurity to parts of the community, which can result in losing the ability to see the specific contents from that side of society. On the other side, the ability to track changes in public discussion makes it possible to construct and analyze time series shading light in different aspects of forming public conversations and its evolution over time. These time series can be used to detect mis- and dissemination in very early stages. Furthermore, coupling these time series with other social, political, economic, or natural events and time series can give a better picture of causal links between different factors and society's responses. One main challenge, however, on this path is researchers' and policymakers' access to the data that can be used to extract public conversation and discussion. Since many of these discussions are forming and living on commercial social media platforms, the data collection procedure is not always straightforward. For instance, it is usually the platform manager who decides which part of the data can be accessed. Once the data are available, the methods described earlier can be used to get a better understanding of people's concerns, which in turn can be used in the fight against mis- and disinformation. In a more general application, the outcomes can help strengthen democratic procedures in policy- and decision-making.

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