Examining the COVID-19 Infodemic on Twitter: A Social Network Analysis in the Context of Thailand

Abhibhu Kitikamdhorn[1] and Pirongrong Ramasoota[2]

Faculty of Communication Arts, Chulalongkorn University, Bangkok 10330 Thailand[1]

Office of the National Broadcasting and Telecommunications Commission (NBTC), Bangkok 10400 Thailand[2]

*Corresponding Author E-mail: abhibhu@hotmail.com

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Abstract

Previous research on the COVID-19 infodemic has focused on the Western world and a limited time frame. This study aims to bridge the gap by examining the infodemic in a different context - Thailand - over a longer period, from December 31, 2019 to July 31, 2021. The study's objectives are to: understand how COVID-19 information pollution is spread on Twitter, assess the effectiveness of counter-narratives in reaching users, and identify the most common types of information pollution and trends. Content, sentiment, and social network analyses were conducted to achieve the study's objectives.

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** The Research Ethics Review Committee for Research Involving Human Subjects: The Second Allied Academic Group in Social Sciences, Humanities and Fine and Applied Arts at Chulalongkorn University has approved the execution of the Research Project Number 231/64 COVID-19 INFODEMIC AND SOCIAL MEDIA PLATFORMS IN THAILAND by Abhibhu Kitikamdhorn (Certificate of Research Approval: COA No. 271/2565).

The results showed that five categories of disinformation were the most common in the dataset: politics (45.70%), medical information (21.31%), vaccine_politics (16.33%), conspiracy_theory (7.68%), and vaccine_medical_info (6.28%).Most nodes interacted with information pollution (59.51%). Only a small proportion of the nodes engaged with debunking/fact-checked messages (16.87%) or both information pollution and debunking/fact-checked messages (23.61%). The results also revealed that the communication network was not completely isolated, as there were nodes that are well-connected to both information pollution and debunking/fact-checked messages. This suggested that users may be exposed to diverse content, even if they were primarily interacting with information pollution. Understanding the problem in its actual context could lead to the development of appropriate and effective responses to the current and future infodemic.

Keywords: Infodemic, Disinformation, Misinformation, Covid, Social Network Analysis, Twitter, Thailand

Introduction

The world has undergone significant changes due to the COVID-19 pandemic since its outbreak in late December 2019. While social media and digital platforms have been utilized by global, national, and local governing bodies for health communication with the public, it is apparent that social media is a hotspot for the spread of disinformation and misinformation concerning COVID-19. One of the significant challenges brought by the pandemic is the “infodemic” or “parallel pandemic of disinformation,” as described by the UN Secretary-General as a “communications emergency” (United Nations, 2020).

A systematic review of research publications about the COVID-19 infodemic on social media found that most of the studies only looked at short periods of time, with the longest study covering 123 days and with a focus on English content and Western contexts. This study aims to bridge the gap by examining the infodemic in a different context - Thailand - over a longer period, from December 31, 2019 to July 31, 2021.

While Western countries prioritize human rights and freedom of expression, Southeast Asian countries use a different approach to combat the infodemic. These countries, including Singapore and Thailand, adopt measures such as anti-fake news laws and restrictions to control the spread of COVID-19 disinformation. However, their coercive approach, particularly censorship, is frequently criticized for being politically motivated. Studying the infodemic in Thailand would expand the current understanding of the issue beyond Western contexts. It would also help us to better understand the issue in a social context where a significantly different COVID-19 management scheme has been used than what is presented in the existing literature.

Thailand was once considered a top performer in COVID-19 management and recovery in the initial phase of the pandemic (Issac et al., 2021; Pornbanggird, 2020). However, the government's early success in managing the pandemic was not sustained. The government's communication on critical issues, particularly COVID-19 management and vaccine management, eroded public trust and led to widespread dissatisfaction. This dissatisfaction has led to protests and demands for the government's resignation, with thousands of people protesting against the government's handling of the COVID-19 situation, vaccine management, and the economic repercussions (Phasuk, 2021; Reuters in Bangkok, 2021). For example, in the early days of the COVID-19 outbreak, social media users shared information about the high lethality and contagiousness of the virus. However, the Minister of Public Health made statements that downplayed the severity of the virus. He stated that the Ministry of Public Health could handle it and referred to it as a “krajok” virus (meaning a weak virus) in December 2019 (The Nation, 2021). In January 2020, he even dismissed COVID-19 as “just a cold” (BBC, 2021). These remarks received widespread criticism and led to a decrease in public trust in the government. Pavel Slutskiy and Smith Boonchutima’s study on the government’s health communication during the pandemic presents an example of a tweet that stated, “China and Hong Kong have declared a state of emergency. The US has sent planes to evacuate people from China. However, this person still claims it’s just a common cold. When will they start taking it seriously?” According to the analysis, individuals who lacked trust in the government turned to alternative sources of information, which were frequently unreliable. This made it even more difficult for the government to contain the virus (Slutskiy & Boonchutima, 2022).

During the lockdown phase, the government also faced an uphill battle in legitimizing its public health measures, such as extending the emergency decree and limiting mass gatherings, as the public perceived these measures to be politically motivated. According to a news report, the emergency decree was implemented on March 25, 2020, to manage the COVID-19 situation and had since been extended numerous times. However, a total of 1,447 individuals were charged with violating the decree, mainly for participating in mass gatherings (อันนา หล่อวัฒนตระกูล และ เยี่ยมยุทธ สุทธิฉายา, 2565). In fact, Thai had a long history of restrictive measures to manage disinformation, including censorship on social media. This approach continued during the pandemic. The Thai government's efforts to curb fake news have been criticized for infringing on freedom of expression, especially during the COVID-19 pandemic (Human Rights Watch, 2020a).

The government's politicization of messages related to COVID-19, particularly in a climate of public distrust, created confusion as various conflicting discussions or alternative narratives concerning the issue emerged. This scenario was particularly probable in an atmosphere where people were already skeptical of the government's motives, making it challenging for people to determine what to believe and potentially resulting in poor health-related decisions.

At the time of writing, previous studies have focused on the pandemic itself, rather than the spread of COVID-19 disinformation in Thai context (Goodwin et al., 2020; Marome & Shaw, 2021; Maude et al., 2021). To address this knowledge gap, this study aims to investigate the infodemic in Thailand, which has a very different social context, COVID-19 situation, and responses than those in the West. The study’s objectives include gaining insights into how COVID-19 information pollution is spread and how effective counter-narratives are in reaching social media users during the pandemic, along with identifying prevalent types of information pollution and trends. The knowledge gained from this study can be used to improve policymaking regarding pandemic communication, media, and information literacy. Understanding the problem in its actual context could lead to the development of appropriate and effective responses to the current and future infodemic.

Literature Review

Conceptualizing Infodemic and Disinformation

The terms misinformation, disinformation, and fake news have been used interchangeably by different groups, such as the media, politicians, and scholars. This has led to ambiguity and confusion about the meaning of these terms. The complexity of the problem and the lack of a shared understanding of the problem were reflected in this ambiguity. Because there was a need for a unified terminology and typology to understand the phenomenon, various attempts have been made to establish a comprehensive framework. Initial efforts were concentrated on establishing precise definitions and criteria for evaluating different types of information. Scholarly works on defining fake news and related concepts emphasized that the intention behind the dissemination of information and the factuality of the information were defining common characteristics (Tandoc, 2019). To illustrate, the information disorder framework was created to provide an explanation and a definition of the phenomenon, using harmful intention and the degree of falsity as key criteria (Wardle & Derakhshan, 2018; Wardle, 2019). This has gained widespread adoption in academic and policymaking circles as a means of distinguishing between different types of information pollution. One notable example was the adoption of Wardle and Derakhsha''s framework by UNESCO, which used it to develop a journalism handbook and module (Ireton & Posetti, 2018).

Due to the pandemic, there has been a noticeable change in the approach towards developing a framework that comprehensively addressed the issue at hand, rather than focusing on creating specific criteria for classifying subtypes. UNESCO and its partners argued that existing current framework, relying on intention as a criterion needed to be refined because as it could be challenging to identify the sources and spreaders of problematic information, let alone their intentions. Therefore, a new framework called the "disinfodemic" was created, emphasizing the importance of the targets or interpreters of information rather than the producers or spreaders because the impacts of information pollution concerning COVID-19 could occur regardless of intentions (Bontcheva et al., 2020; Posetti & Bontcheva, 2020). Under this framework, disinformation was used as a general term for false or misleading content that could cause harm, regardless of intentions. To prevent confusion, the term disinformation will be defined according to UNESCO's framework from this point forward, and the terms “information pollution” and “infodemic” (World Health Organization, 2020) will be used as a hypernym in this article.

Filter Bubble and Echo Chamber

In social media, users had the power to choose what to see and whom to connect with, creating their own social networks. However, this could lead to individuals becoming trapped in a filter bubble or echo chamber, particularly in extreme cases. Scholars have suggested that echo chambers are created by the interaction of two factors: technological and psychological. Social media platforms relying on advertising revenue have used machine learning algorithms to provide users with personalized information and advertisements based on their past behavior. Consequently, there was a possibility that users got exposed only to information that confirmed their preexisting beliefs and preferences rather than a diverse range of information (Stephens-Davidowitz, 2018; Wieringa, 2020). Studies pointed out that disinformation could spread more widely in social media echo chambers (Cinelli et al., 2021; Törnberg, 2018) as people tended to conform to what was perceived to be the mainstream view (Flaxman, Goel, & Rao, 2016). Users' engagements were linked to the speed and reach of disinformation propagation, as these interactions shaped network structures that, in turn, influenced how disinformation was spread.

Another concept that could be used to describe a phenomenon similar to an echo chamber was informational homogeneity. It suggested that similar types of disinformation are often linked together. For example, one piece of disinformation may lead to other pieces of disinformation. If users were part of a closely connected group of like-minded individuals who shared the same type of content, and had few connections with those who offered opposing or fact-checked information, this resulted in high levels of informational homogeneity (Röchert et al., 2021). Based on these, research hypothesis 1 (RH1) is made.

RH1: drawing from the concepts of echo chamber and informational homogeneity, it is possible that a homophily network structure may emerge, with network graphs consisting of subgraphs of nodes sharing similar attributes. This is because people tend to form social networks with like-minded individuals, often resulting in a largely isolated community.

Understanding Users' Engagements with Information Pollution

While humans could process information analytically, studies have shown that people generally lacked the ability to accurately identify false information. Instead, they often relied on heuristics, or mental shortcuts, to assess information from their social media "friends" and opinion leaders (Metzger, Flanagin, & Medders, 2010 as cited in Duffy et al., 2019; Shu et al., 2020). Additionally, a study has found that influential individuals often played a vital role in amplifying the spread of disinformation on social media and attracting a large amount of social media engagement (Brennen et al., 2020). This was because their posts were more likely to be seen and shared by their followers. People tended to trust the information they saw on social media, especially if it came from someone they knew or respected because they believed that their social network was a reliable source of information.

Studies in the fields of psychology and communication have previously demonstrated that negativity bias was one of the causal factors for selective exposure to online news, and negative information, e.g., a threat to people's lives and security in a community and tended to attract more attention and be more arousing than positive information. Based on the notion, humans were naturally inclined to believe negative information and to be more aroused by it than by positive information. This assumption was supported by many experimental results. For example, studies have shown that people were more likely to pay attention to negative news stories about healthcare than about immigration. This was likely because people were more likely to see healthcare as a threat to their well-being. This bias could be explained by the fact that people had a natural inclination to seek out potential threats in their environment, and negative information held a psychological value of being a potential threat. Consequently, negative information was more likely to grab people's attention and caused more arousal than positive information (Van der Meer et al., 2020; Vasu et al., 2019).

Based on these, the following RHs are proposed.

RH2: Based on the concepts of negativity bias and informational negativity bias, it is likely that the negative sentiment would dominate the Twitter network and gain a higher level of engagement, compared to those of positive or neutral content.

RH3: According to the studies mentioned in this section, it is possible that influential accounts on social media, which are those with a large number of followers, could play a significant role in the spread of COVID-19 disinforamtion.

Methodology

The way that researchers choose to study echo chambers can have a big impact on the results of their studies. A review of 55 studies on social media echo chambers published between 2011 and 2020 by Borge and Terren found that studies that used digital trace data (such as data from social media platforms) were more likely to find evidence of echo chambers than studies that used self-report data (such as surveys) (Terren & Borge-Bravo, 2021). Previous studies have shown that social network analysis (SNA) can be used to identify the distinct characteristics of disinformation networks in Twitter, resulting in the development of a deep learning-based method for identifying key influential nodes in the network (Cheng et al., 2021). Therefore, since this study's primary objective is to investigate the spread of COVID-19 disinformation through digital traces, a network-based approach to analyze Twitter data that reflects actual user interactions can be adequately used to explore whether an echo chamber effect is involved in the propagation of the COVID-19 infodemic in Thailand or not.

To fulfil the research objectives, analyses of content, sentiment, and social network are conducted.

Data Collection

Twitter data could be accessed through application programming interfaces (APIs), but with public data only, so this study focuses on only public data. The data was collected over a period of 19 months, from December 31, 2019, to July 2021. The process of data retrieval was done in two steps. The first step involved fetching fact-checked data from selected fact-checkers within the study time frame using CrowdTangle. After this, a labeling/tagging process was done to filter out noise. In the second step, Twitter API for Academic Research was used to fetch the actual Twitter data using keyword sets derived from the first batch. The dataset was then subjected to filtering, topic labeling, and sentiment analysis processes before commencing the network mapping process.

After the researcher had preliminary explored fact-checking bodies operating in Thailand, three fact-checkers were selected based on their clear-cut text-based archives. These were the Anti-Fake News Center Thailand (AFNC Thailand), which was run by the Ministry of Digital Economy and Society, AFP Fact-Check Thailand, and อ๋อ มันเป็น

อย่างนี้นี่เอง by อาจารย์เจษฎ์ (OhISeebyAjarnJess), a Facebook page run by Jessada Denduangboripant, a local scientist and university lecturer known for his role in fact-checking and investigating with scientific evidence and verification. These three fact-checkers provided clear-cut text-based archives compared to other fact-checkers in Thailand, such as CoFact, which used a crowdsourcing approach, and SureAndShare, which used a non-text based approach—providing video content.

Content Analysis

The researcher utilized content analysis in both batches of data retrieval: the first batch focused on fact-checked archives, while the second phase examined the actual Twitter dataset. In order to form the category, the researcher drew from previously identified themes of COVID-19 disinformation found in literature (Brennen et al., 2020; Posetti & Bontcheva, 2020), which were then applied to the aforementioned fact-checked corpus (see Table 1 for example). The acquired text messages were processed by word tokenization, keyword frequency measuring, and content categorization. In other words, the text messages were divided into chunks, and keywords were extracted and mapped onto the developed categories. Computer programs, such as Python with related Natural Language Processing packages such as PyThai and Microsoft Excel, are used in these processes.

Table 1. Themes of COVID-19 information pollution

No.	Themes	Examples from fact-checked dataset (translation in square brackets)
1.	**Origins and spread of the virus** (i.e., content about the origins/causes of the virus and/or content about the spread of the virus in certain areas or communities without statistics; content blaming actors/causes)	-"...COVID-19...ไม่ใช่ไวรัส แต่เป็นแบคทีเรียที่สัมผัสกับรังสี 5G..." [COVID-19 is caused by bacteria and spread by 5G] -"ไวรัสโคโรน่าลงเบตงเหตุนักท่องเที่ยวจีนชุก" [coronavirus spread in Betong (Thailand) as Chinese tourists swarm]
2.	**False and misleading statistics**	-"...สมุทรปราการอันตราย...ติดเชื้อCovid-19...รักษาตัว...1คน" [Samut Prakan is dangerous... one infected cases]
3.	**Economic impacts**	"...หลายๆบริษัทปิดตัว พนักงานตกงานกันเต็มเลย ถึงกับต้องมานั่งรออาหารจากคนที่ใจดี..." [several companies have closed, employees are laid off...lining up for free food]
4.	**Vaccines**	"เปิดจองวัคซีนล็อตพิเศษสุด VIP..." [open vaccine booking, special lot, for VIP]

No.	Themes	Examples from fact-checked dataset (translation in square brackets)
5.	**Medical information** (e.g., symptoms, diagnosis, treatment, and recommendations)	“กัญชา...เคลือบ...ปอดทำให้เชื้อไวรัสโควิด-19 ไม่สามารถฝังตัวได้” [cannabis...coats...lungs, so COVID-19 virus cannot damage our lungs]
6.	**Impacts on society and the environment**	“พยาบาลศิริราช...บอกว่า...ตุนของไว้...จะมีการปิดเมืองแล้ว...” [Siriraj’s nurse...said...we should stock up...cities will be in lockdown...]
7.	**Public responses and politicization**	“พรกฉุกเฉิน...ห้ามใช้อินเตอร์เน็ตว่าร้ายรัฐบาล...” [the emergency decree prohibits the use of internet to criticize the government]
8.	**Content driven by fraudulent financial gain** (+trying to steal personal information)	“ทำตามนี้ 5,000 บาทเข้าแน่นอน www.เราไม่ทิ้งกัhttp://xn--q3c.com/...โทร 1111 ได้เงินทันที” [follow this to get 5,000 THB... www.เราไม่ทิ้งกัhttp://xn--q3c.com/...call 1111 to get money immediately]

No.	Themes	Examples from fact-checked dataset (translation in square brackets)
9.	**Celebrities/prominent figures**	“ราชินีฯ…ทรงพระประชวรด้วยโรคโควิด-19…” [the queen has been sick with COVID-19]
10.	**Others** (e.g., foreign affair)	“อิตาลีฝังศพที่ติดโรคโควิด-19 นับพันศพในสภาพนี้…” [thousands of COVID-19 infected bodies were buried like this in Italy]

Note. Translations of the original text are displayed in square brackets.

Sentiment Analysis

The purpose of utilizing sentiment analysis is to overcome the methodological constraint of social network analysis (SNA), which represents the connections between nodes without examining the content. As a result, evaluating the sentiments expressed in the content could provide insight into users' opinions and attitudes towards the topics being discussed.

A semi-automated approach was used to conduct sentiment analysis. The National Electronics and Computer Technology Center’s (NECTEC) S-Sense, a sentiment analysis solution using machine learning, was used to perform automated initial sentiment analysis. The machine learning model used a corpus derived from Thai language used in social media to evaluate text-based input and provide the result as either negative, neutral, or positive (NECTEC, 2016; 2019a; 2019b). The results were then manually fine-tuned by the researcher. On social media, people may use natural language in complex ways when discussing

COVID-19, which may include sarcasm or using words in unusual ways. For example, the word “หาย” typically means “missing” or “lost” and conveys negative sentiment. However, in the context of COVID-19, it could indicate "recovery" and convey positive sentiment. Due to such nuances, the machine learning model may sometimes misinterpret the input. Therefore, the results were carefully reviewed and corrected based on the actual meaning and tone of the text.

After getting results from the initial analysis, the next step was to convert the findings into a supervised machine learning text classification model , which determined its precision. In this sense, the labeled data extracted from the S-Sense outcomes was employed to train the algorithm how to classify the text-based input into three groups: negative, neutral, and positive. Python’s Scikit-learn machine learning library, also known as sklearn, which could conduct text classification, was used. The performance of the classifier was then evaluated against the actual Twitter dataset using standard metrics for measuring a model’s prediction performance. These metrics were:

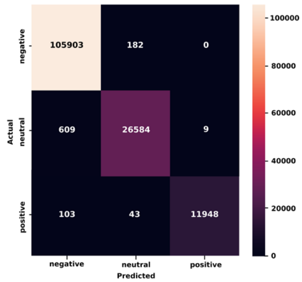
Accuracy: the calculation of the overall accuracy or proportion of correct predictions.

Precision: the measurement of the number of predictions made that are actually correct.

Recall: the calculation of the number of instances of the positive class that are correctly predicted.

F1 score: an accuracy measure derived from the harmonic mean of precision and recall (Igual & Seguí, 2017; Sarkar, 2016).

The model evaluation process yielded an overall accuracy rate of 0.99 (99%) for the Twitter data (see Figure 1).



	precision	recall	f1-score	support
negative	0.99	1.00	1.00	106085
neutral	0.99	0.98	0.98	27202
positive	1.00	0.99	0.99	12094
accuracy			0.99	145381
macro avg	0.99	0.99	0.99	145381
weighted avg	0.99	0.99	0.99	145381

Figure 1 Model evaluation of the sentiment analysis of the Twitter dataset

Social Network Analysis

To conduct SNA, it was necessary to prepare the dataset for network mapping tools. Nodes were labeled with a node ID, and relationships between sources and targets were identified. Tools such as Gephi and NetworkX (a Python package) were used for network analysis and visualization. In this study, the network of information diffusion was analyzed, and for network visualization, a node referred to a Twitter account involved in the networks, and a link indicated how a piece of information was transmitted within the network.

SNA was utilized to investigate network structures to determine if they exhibited significant clusters or substructures such as segregated substructures that indicated the presence of echo chambers, or cross-cutting communication patterns that suggested no echo chamber. Community detection methods, such as modularity and bridge removal, were employed to identify communities or clustering patterns. Additionally, the study analyzed the key actors in the networks, along with their common properties or assortativity

(Menczer et al., 2020; Scott & Carrington, 2014). Essentially, network visualization was created to depict the structures of relationships within networks that enabled information diffusion, along with influential nodes within the networks.

Human Subjects Protection for Social Media Users

In the visualization, the names of the nodes were excluded to avoid the risk associated with identifying those involved in the network. In the discussion of the findings about the influential nodes, descriptions of the nodes (such as news media accounts, public figures, or news (Facebook) groups) were given instead of node names. Overall, to diminish the risk involved with relevant users in the dataset, no screenshots of posts and IDs of Twitter accounts were shown.

Results

Common Themes of the Infodemic

This study utilized the common themes proposed in previous literature, but modifications were made to account for the distinct infodemic phenomenon observed in the collected datasets. Figure 2 showed the distribution pattern of the Twitter dataset. Five categories stood out in the dataset, while the rest were sparsely populated. The categories were: politics (45.6971%), medical_info (21.3128%), vaccine_politics (16.3253%), conspiracy_theory (7.6795%), and vaccine_medical_info (6.2839%). These categories ranked first to fifth, respectively, in the Twitter dataset. It is worth noting that the Twitter dataset contained debunking/fact-checked messages that could be grouped into three distinct themes (see Table 2): debunk: tweets containing debunking messages without evidence, debunk_3rd_person_effect: tweets containing debunking messages reflecting that the tweeter perceives the others to fall under the influence of COVID-19 information pollution, debunk_satire: satires on pieces of information pollution , and fact checked: tweets containing debunking messages with evidence or debunking messages from a fact-checker. The appearance of messages containing satire and third-person effect hinted at the overall sentiment expressed in the dataset.

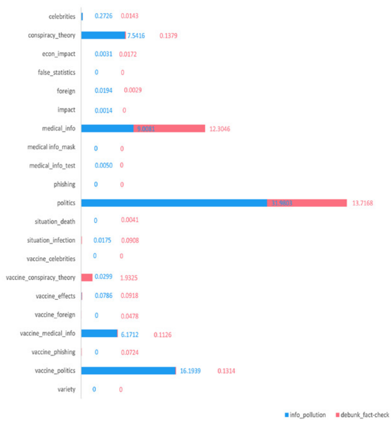


Figure 2 Comparison between the fact-checked messages and information pollution in the Twitter dataset (in percentage)

Table 2 Analysis of the debunking/fact-checked messages within the Twitter dataset

Category	Count
debunk	141717 (24.3701%)
debunk_3rd_person_effect	2185 (0.3757%)
debunk_satire	13783 (2.3702%)
fact-checked	9079 (1.5613%)

When the fact-checked and Twitter datasets were plotted against the temporal sequence of COVID-19 confirmed cases, the resulting chart showed a prevailing trend between the Twitter dataset and COVID-19 confirmed cases in 10 out of 19 months , which spanned from August 2020 to July 2021 (see Figure 3). This trend indicated that as the number of reports on COVID-19 confirmed cases increased, the number of instances of information pollution also increased, and the reverse was also true. It could be deduced that the dynamics of the infodemic were noticably affected by contextual factors such as the pandemic and its responses.

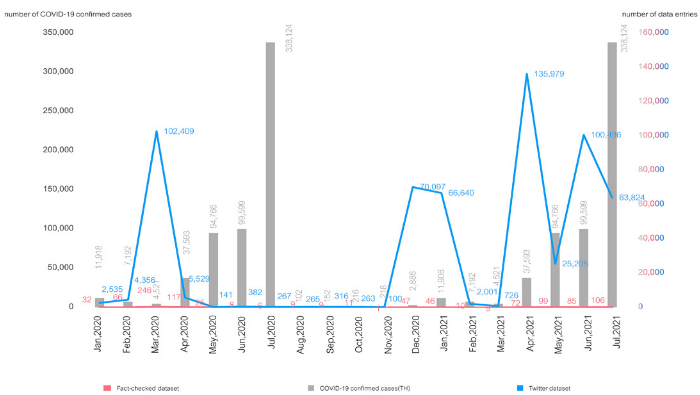


Figure 3 Comparison between COVID-19 confirmed cases and trends in the fact-checked and Twitter infodemic datasets

Sentiment Analysis

Looking at the assessment of sentiments expressed in the Twitter dataset, the results showed a highly unbalanced distribution as both the debunk/fact-checked and information pollution messages were predominantly negative. The most densely populated negative theme was "politics" (see Figures 4-6). A probable explanation for the manifestation of negativity was that there was a tendency for the communication environment where users could preserve their anonymity to encourage aggressive behavior and negativity. In other words, in Twitter's absence of a "Real-Name Policy," a requirement for users to use only identifiable usernames, users tended to be openly aggressive, even with hate speech (Mondal et al., 2017; Peddinti et al., 2014). The evidence also indicated that social media anonymity could result in other related problems, such as the use of anonymous social media accounts to conduct information operations (IOs) using COVID-19 disinformation to support the government and attack dissenters (วงศ์พันธ์ อมรินทร์เทวา, 2565ก, 2565ข).

However, evidence showed that the anonymity of Twitter had the inherent virtue of being a safeguard for free speech in societies where the chilling effect was fairly strong, such that self-censorship was the norm for people to avoid being considered political dissidents. This fostered a subculture of anonymous social media communication, e.g., the spread of political messages "from a friend" ("มิตรสหายท่านหนึ่ง"), political satire, and public recognition of anonymous social media influencers (Chainan, 2020; Wantanasombut, 2019).

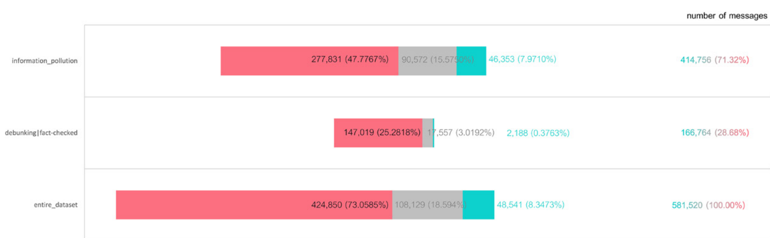


Figure 4 Sentiment analysis of the entire Twitter dataset

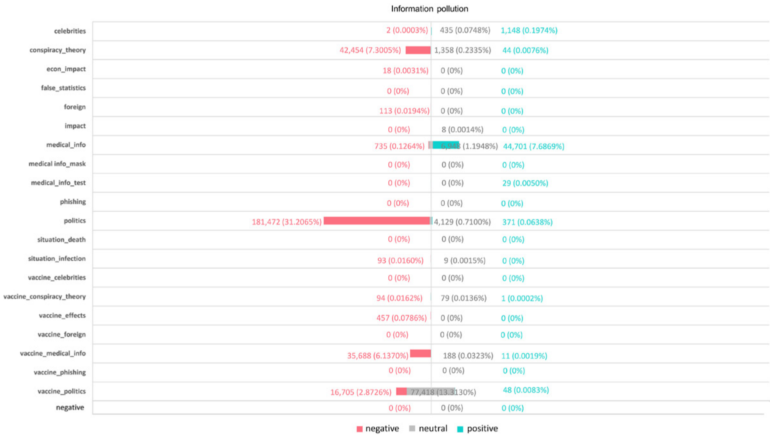


Figure 5 Sentiment analysis of only the information pollution data entries in the Twitter dataset

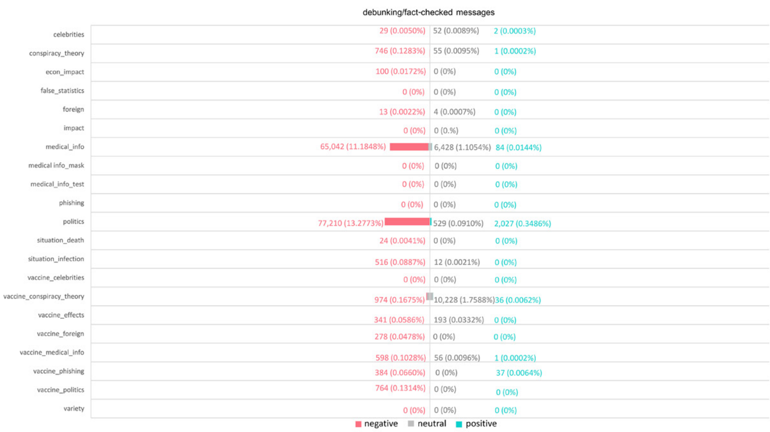


Figure 6 Sentiment analysis of only the debunking/fact-checked data entries in the Twitter dataset

Social Network Analysis

The choice of a force-directed network visualization method was known to prioritize the creation of visually appealing graphs with minimal crossing lines (Kobourov, 2014). Among different types of force-directed layouts, ForceAtlas2 stood out for its ability to illustrate structural clustering and modularity by simulating movement between nodes, which was achieved through balancing the forces of attraction and repulsion (Jacomy et al., 2014). The algorithm utilized for drawing the graphs emphasizes the visualization of important nodes by clustering them at the center of the network (Khokhar, 2015), based on the similarities and/or differences in the data (Cherven, 2013). As a result, the force-directed layout algorithm, ForceAtlas2, was employed to draw the network graphs.

Modularity

To test RH1, the research measured modularity, which was a technique used to identify patterns of clustering within networks. Essentially, modularity detected clusters (also known as communities) by comparing the density of links within a cluster against an expected baseline calculated through mathematics (Scott & Carrington, 2014). In other words, it indicated "the number of communities present within a graph" (Cherven, 2013). By grouping and color-coding the nodes, the modularity computation revealed the clustering patterns present in the network structure.

The analysis found 14 communities, but only two of them (purple [0] and green [1]) were densely populated and easy to see (see Figure 7 and Table 3). These two communities made up more than 80% of the network, while the rest were scattered. Nodes' sizes were computed based on the degree values, so the bigger nodes signified higher engagement.

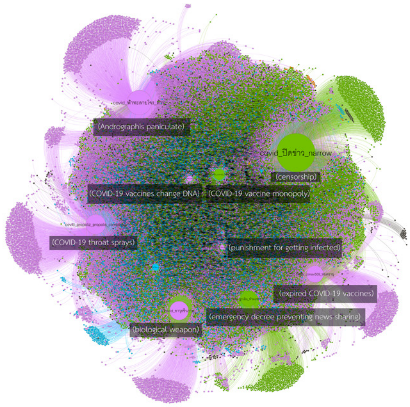


Figure 7 Network visualization of the Twitter dataset based on modularity classes

Table 3 Comparison between the modularity classes of nodes interacting with debunking/fact-checked and information pollution messages within the Twitter dataset

Modularity class ID	Node count (modularity classes)	Debunking| fact-checked tags	Information pollution tags	Both tags
0 (purple)	106,534 (54.262168%)	20,892 (10.641159%)	58,350 (29.720066%)	27,292 (13.900943%)
1 (green)	63,672 (32.430781%)	8,650 (4.405802%)	43,767 (22.292342%)	11,255 (5.732637%)
12 (light blue)	12,635 (6.435528%)	6 (0.003056%)	9,457 (4.816841%)	3,172 (1.615631%)

Modularity class ID	Node count (modularity classes)	Debunking| fact-checked tags	Information pollution tags	Both tags
2 (black)	11,353 (5.782552%)	3,575 (1.820895%)	3,667 (1.867755%)	4,111 (2.093902%)
13 (orange)	2,112 (1.075729%)	5 (0.002547%)	1,581 (0.805269%)	526 (0.267914%)
sum of the remainder	26 (0.013243%)	2 (0.001019%)	20 (0.010187%)	4 (0.002037%)
Total	**196,332 (100%)**	**33,130 (16.874478%)**	**116,842 (59.512458%)**	**46,360 (23.613064%)**

Note. The data entries (nodes) are grouped into 14 different modularity classes ranging from number 0 to 13

Upon closer examination of the two largest components, it was evident that there were nine nodes that had a significant level of engagement (as shown in Figure 8). These nodes were involved in six different message categories: 1) medical_info: covid_ฟ้าทะลายโจร_ต้าน, covid_propoliz_propolis_combined; 2) vaccine_medical_info: วัคซีน_ctmav509_หมดอายุ; 3) politics: covid_ติด_ครู_ไม่ป้องกันตัวเอง_ลงโทษ, พรก_ฉุกเฉิน_ห้ามแชร์ข่าว, covid_ปิดข่าว_narrow; 4) vaccine_politics: covid_ผูกขาดวัคซีน_covid_วัคซีน_อย_ผูกขาด; 5) conspiracy_theory: covid_อาวุธชีวภาพ; 6) vaccine_conspiracy_theory: covid_วัคซีน_เปลี่ยน_dna.

In the purple cluster, six nodes were more prominent than the others, and there were three high-engagement nodes in the green cluster. Two of the largest nodes in the purple cluster fell into the "medical_info" category (i.e., medical information related to COVID-19). The first node represented claims about the use of Andrographis paniculate to prevent COVID-19, while the second node represented claims about COVID-19 throat sprays. The node representing claims politicizing COVID-19 measures, particularly claims about punishment for teachers if they got infected, fell into the category of “politics” (i.e., politicization of COVID-19 related issues), and the one representing claims about the use of expired COVID-19 vaccines fell into the “vaccine medical_info” category (i.e., medical information about COVID-19 vaccines). Another node pertained to COVID-19 bioweapon claims and fell into the “conspiracy_theory” category, while the smallest node in the purple cluster pertained to claims that COVID-19 vaccines changed human DNA and fell into the "vaccine_conspiracy_theory" category. The biggest node in the green cluster representing the censorship of COVID-19 reporting fell into the “politics” category. The smaller two noticeable nodes in the green cluster fell into the “politics” and “vaccine_politics” categories respectively. The one representing claims about an emergency decree preventing news sharing fell into the “politics” category, and the one representing claims about COVID-19 vaccine monopoly fell into the “vaccine_politics” category.

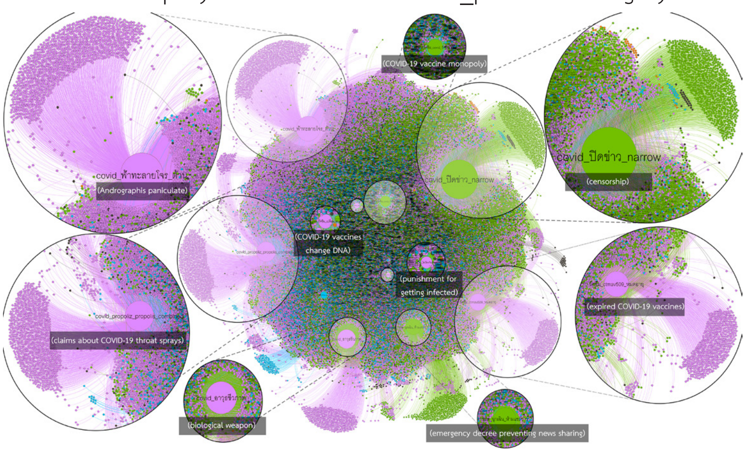


Figure 8 A zoom in image of the high engagement nodes within the two biggest components of the Twitter network visualization

Table 3 above also showed a clear trend that the majority of nodes interact with information pollution (59.512458%), while only a small proportion of the nodes engage with debunking/fact-checked messages (16.874478%) or both information pollution and debunking/fact-checked messages (23.613064%). The same trend could be observed in each cluster in the network. This indirectly implied that a significant proportion of the debunking/fact-checked messages did not reach those interacting with the information pollution.

Betweenness Centrality

In essence, betweenness centrality calculated the extent to which a node was in an intermediary position or in "between" position, allowing others to connect or information to pass through it (Cherven, 2013). Overall, the calculation of betweenness centrality for the Twitter network indicated that the network structure was not entirely an echo chamber because there were a modest number of nodes occupying the "bridge" positions (see Table 4). The majority of "bridge nodes" here (22.509897%) contained both debunking/fact-checked and information pollution tags. This implied that they not only allowed information to flow between clusters by connecting different tags within the same categories but also between debunking/fact-checked and information pollution tags. For this reason, the network could be said to have a somewhat cross-cutting spread pattern. In other words, there was a chance of Twitter users encountering content concerning COVID-19 from different viewpoints or sources with different attributes than themselves.

A deeper look at the "bridge nodes" within the Twitter network showed that the top five percent of the "bridges" (4,278 nodes) could be divided into 11 categories (see Table 5 below), and "UGC," user-generated content, "S.Korea focus," and "politics" were the top three. In the context of Thailand, Twitter has been a platform for K-pop fandom and political communication. A renowned Thai political scientist observed that injustice in the K-pop industry inspired South Korean accounts to tweet or retweet about political injustice in Thai society. This raised political awareness among younger users who were typically K-pop fans (เทวฤทธิ์ มณีฉาย, 2021). The political awareness of Twitter users was evident in the Twitter dataset, where "politics" messages were among the most common. South Korean focus and politics nodes were among the top three "bridge" nodes in terms of frequency, which suggested that they occupied prominent positions in the network and allowed information to flow between different clusters. Examining the top 0.01 percent of nodes with high betweenness centrality (10 out of 85,570 nodes), it was discovered that they had a high number of engagements, indicating their prominent positions in the network, and the majority of them engaged with both debunking/fact-checking and information pollution messages (7 out of 10 nodes) (see Table 6). This once again emphasized the key role of accounts producing general user-generated content and South Korea focus content in bridging between different clusters. Bridge nodes played a crucial role in enabling the flow of information between topics and clusters. Users connecting with the “bridges” had the chance to encounter COVID-19 content from various viewpoints or sources with different attributes.

In summary, due to the limited number of bridge nodes, Twitter's network structure indicated the presence of two distinct echo chambers - one for debunking/fact-checking and the other for information pollution. suggested that homophily was present and supported the RH1.

Table 4 Analysis of nodes' betweenness centrality scoring based on the modularity classes within the Twitter

Modularity class ID	Node count (betweenness centrality)	Debunking factchecked tags	Information pollution tags	Both tags
0 (purple)	49,162 (25.040238%)	3,793 (1.931932%)	18,264 (9.302610%)	27,105 (13.805696%)
1 (green)	22,516 (11.468329%)	312 (0.158914%)	10,968 (5.586456%)	11,236 (5.722959%)
12 (light blue)	6,868 (3.498156%)	0 (0%)	3,705 (1.887110%)	3,163 (1.611047%)
2 (black)	5,952 (3.031600%)	759 (0.386590%)	1,225 (0.623943%)	3,968 (2.021066%)
13 (orange)	1,066 (0.542958%)	0 (0%)	541 (0.275554%)	525 (0.267404%)
sum of the remainder	6 (0.003056%)	0 (0%)	2 (0.001019%)	4 (0.002037%)
Total	**85,570 (43.584337%)**	**4,864 (2.477436%)**	**34,705 (17.676691%)**	**46,001 (23.430210%)**
Grand total	**196,332 (100.000000%)**			

Table 5 Categories of the high betweenness centrality nodes within the top five percent of the Twitter dataset

Rank	Category (nodes)	Count	Description
1.	UGC	4153	"UGC" refers to an account producing user-generated content in general.
2.	S.Korea focus -S.Korea focus -trading, S.Korea focus	(79) 78 1	"S.Korea focus" refers to an account that focuses its content on South Korea related content such as K-pop idols, celebrities, artists, and tourist attractions.
3.	Politics	27	"Politics" refers to an account that focuses its content on politics.
4.	News media -online news media -online newspaper	(5) 4 1	-"Online news media" refers to an account representing an online news media outlet. -"Online newspaper" refers to an account representing a newspaper company.
5.	Trading	4	"Trading" refers to an account that focuses its content on selling goods/providing services.
6.	Fact-checker	3	"Fact-checker" refers to an account representing a fact-checker.

Rank	Category (nodes)	Count	Description
7.	Lottery	2	“Lottery” refers to an account that focuses its content on lottery.
8.	Governmental body	2	“Governmental body” refers to an account representing a government organization.
9.	Public figure	1	“Public figure” refers to an account representing a public figure or a fan club of a public figure.
10.	Review	1	“Review” refers to an account that focuses its content on reviewing products/services.
11.	Business	1	“Business” refers to an account representing a business.

Table 6. Top 0.01 percent of high betweenness centrality nodes within the Twitter dataset

Rank	Category (nodes)	Verified	Sum of Followerst	Sum of Tweet count	Sum of Interactions (Retweet, Reply, Quote, Like)	Betweenness Centrality	Category (mess-ages)
1.	Fact-checker	True	516479	187401	0	0.000499	fact-checked
2.	S.Korea focus	False	90	50043	60238	0.000440	conspiracy_theory_origin|debunk_3rd_person_effect
3.	UGC	Falset	2896	3318517	103310	0.000306	debunk|fact-checked|medical_info|politics|vaccine_medical_info|vaccine_politics
4.	UGC	False	16659	4762277	2118	0.000269	Conspiracy_theory_origin|debunk|debunk_3rd_person_effect|fact-checked|politics
5.	UGC	False	31700	12189022	225008	0.000245	conspiracy_theory_origin|debunk|debunk_3rd_personeffect|debunk_satire|fact-checked|medicalinfo|politics|situation_infection|vaccine_medical_info|vaccine_politics
6.	Politics	False	7733	3841926	3733	0.000222	debunk|fact-checked|medical_info|politics
7.	News media	True	74708207	17110162	0	0.000171	debunk|fact-checked
8.	UGC	False	1521	2729603	156943	0.000167	debunk|fact-checked|medical_info|politics|vaccine_politics
9.	S.Korea focus	False	5076	7266887	381984	0.000156	conspiracy_theory_origin|debunk|fact-checked|medical_info|politics|vaccine_medical_info|vaccine_politics
10.	Fact-checker	True	31368	103276	1609	0.000152	debunk|fact-checked

Hub Nodes

To identify important nodes in the network, Hyperlink-Induced Topic Search (HITS), an algorithm used for connection analysis based on eigenvalues, was used to compute the score of "hub and authority." The hub score indicated the quantity of connections to "highly informative nodes or authoritative nodes" a node has (Khokhar, 2015).

Within the Twitter dataset, only six components contained hub nodes. Among the total of 196,119 "hub" nodes, 66.12% of them interacted exclusively with information pollution. 15.99% of hub nodes interacting with only debunking/fact-checked messages belonged to only the biggest component (modularity class ID 6). The rest interacting with both debunking/fact-checked and information pollution messages scattered across the three biggest components (see Table 7). Hence, the RH3 is confirmed as most of the hub nodes were affiliated with the information pollution cluster.

Table 7 Analysis of hub nodes within the Twitter dataset based on modularity classes and message categories

Modularity class ID	Node count (hub)	Debunking|fact -checked tags	Information pollution tags	Both tags
0 (purple)	106454 (54.221421%)	20863 (10.626388%)	58299 (29.694090%)	27292 (13.900943%)
1 (green)	63666 (32.427724%)	8649 (4.405293%)	43762 (22.289795%)	11255 (5.732637%)
2 (black)	11269 (5.739767%)	3525 (1.795428%)	3633 (1.850437%)	4111 (2.093902%)
3 (gray)	0	0	0	0
4 (teal)	0	0	0	0

Modularity class ID	Node count (hub)	Debunking|fact-checked tags	Information pollution tags	Both tags
5 (desaturated red)	0	0	0	0
6 (gray)	0	0	0	0
7 (gray)	0	0	0	0
8 (gray)	0	0	0	0
9 (light red)	6 (0.003056%)	0	2 (0.001019%)	4 (0.002037%)
10 (gray)	0	0	0	0
11 (gray)	0	0	0	0
12 (light blue)	12615 (6.425341%)	5 (0.002547%)	9438 (4.807163%)	3172 (1.615631%)
13 (orange)	2109 (1.074201%)	5 (0.002547%)	1578 (0.803741%)	526 (0.267914%)
Total	196119 (99.891510%)	33047 (16.832203%)	116712 (59.446244%)	46360 (23.613064%)
Grand total	**196332 (100.000000%)**			

Sentiment Network

Table 8 showed that the network was dominated by negative sentiment because there were 195,878 nodes (99.77%) engaging with messages containing negative tags, and the total interactions stood at 61,422,391,264 based on the sum of negative|neutral, negative, positive|neutral|negative, and negative|positive nodes. As a result, RH2 was validated. This hypothesis suggested that negativity had the tendency to attract and hold people's attention due to concepts such as negatively-biased credulity and informational negativity bias.

Table 8 Sentiment Network of the Twitter dataset

Sentiment	Node count	Total interactions
negative|neutral	195,494 (99.57%)	60,931,618,928
positive	272 (0.14%)	11,561,101
positive|neutral|negative	195 (0.10%)	398,216,606
negative|positive	170 (0.09%)	84,795,481
neutral	151 (0.08%)	8,719,213
neutral|positive	31 (0.02%)	8,528,619
negative	19 (0.01%)	7,760,249
Total	**196,332 (100.00%)**	**61,451,200,197**

Note. interactions here refer to the sum of tweets, retweets, replies, quotes, and likes at posting.

Conclusion and Discussion

After reviewing the literature, it has been found that many studies have focused on a single aspect of the problem, such as the common topics of COVID-19 disinformation, and have often been limited to the West and a short period of time. Therefore, this study took into account three distinct phases of the pandemic in a non-Western setting and investigated two primary aspects of the problem, which were the distribution pattern, along with users' engagement with disinformation and their expressed sentiments. Social media data was collected from Twitter, covering a period from December 31, 2019, to July 2021.

Within the dataset, the majority of posts (71.32%) contained disinformation, while the rest were either debunked or fact-checked messages (28.68%) (see Table 9). The most common topics of COVID-19 disinformation found were medical information, particularly herbal remedies, and the politicization of COVID-19 related issues.

Table 9 Analysis of the Twitter dataset based on message categories

Category	Twitter
information pollution	414756 (71.32%)
debunking/fact-checked messages	166764 (28.68%)
Total	**581520 (100.00%)**

Although the network analysis revealed several nodes that facilitated a cross-cutting spread pattern, the overall structure of the network showed two echo chambers: one cluster with information pollution and the other with fact-checked information. These findings supported RH1, which suggested that individuals tended to form social networks with like-minded people and cluster together in an isolated manner, as suggested by previous literature. However, this also indicated that Twitter users were not completely confined to echo chambers, as there was still an opportunity for them to encounter a variety of COVID-19-related content or different sources. The reason for this could be attributed to the distinctive architecture and norm of the platform: Twitter’s hashtag system. The feature enabled users to access a wider range of information sources by aggregating information from various sources into a single topic. This function was widely adopted by Twitter users. In terms of sentiment, Twitter's network was dominated by negative sentiment and such messages tended to gain significant engagement. As a result, the RH2, which suggested that negativity had the tendency to attract and held people's attention due to concepts such as negatively-biased credulity and informational negativity bias, was validated. The RH3 stated that influential nodes in social networks played an important role in the spread of information pollution. This was supported by the results of this study, which showed that a large number of hub nodes interacted mainly with information pollution. It was noteworthy that the results of the social network analysis provided further evidence of the influence of contextual factors, such as the COVID-19 situation, and societal-level factors, such as political atmosphere and polarization, on the infodemic. The presence of natural remedies categorized under the medical_info cluster and the information related to government censorship categorized under the politics cluster were examples that illustrate this point.

To sum up, the study indicated that debunking/fact-checked messages regarding COVID-19 countermeasures are not successfully breaking through echo chambers. This can be attributed to the current political climate and deep polarization in Thailand where the government's communication is often politicized and lacks public trust. The social network analysis conducted in this study supports this claim. The emergence of content about the government's censorship of COVID-19 related information is a case in point. Even though the RHs are supported, it is important to note that further research is needed to confirm the relationship between echo chamber and psychological factors. In other words, user-level factors such as selective exposure, confirmation bias, cognitive dissonance, and political attitude, which play a role in shaping the infodemic, require further study. This is because the literature review gathered for this study is from various fields beyond COVID-19 disinformation, including political communication during elections and from Western countries, rather than Thailand. Therefore, it is possible that these psychological and contextual factors may have different influences when it comes to COVID-19-related issues. Furthermore, as the results of this study are derived from solely a single platform, it is possible that people use different platforms differently, so it is important to explore the phenomenon on other platforms to foster comprehensive understanding of the issue. Understanding the problem in its actual context could lead to the development of appropriate and effective responses to the current and future infodemic. Based on the results, it is evident that relying solely on the dissemination of debunking messages through social media platforms is insufficient to break echo chambers.

Considering the limitations of relying solely on the dissemination of debunking messages through social media platforms, it is crucial to adopt a multi-faceted approach to tackle echo chambers and combat the spread of COVID-19 disinformation in Thailand. This approach should encompass the following strategies:

1. Strengthen media literacy programs: develop comprehensive media literacy programs that target the general public, focusing on critical thinking skills, information evaluation, and source verification;

2. Foster cross-platform collaboration: extend research efforts beyond a single platform to gain a more comprehensive understanding of how people interact with information and echo chambers across various online platforms. This will help identify platform-specific dynamics and inform the design of effective interventions;

3. Engage diverse stakeholders: encourage collaboration between government agencies, media organizations, civil society groups, and educational institutions to jointly address the challenges posed by echo chambers and disinformation. A coordinated effort involving these stakeholders can facilitate the development and implementation of targeted initiatives to promote accurate information and counter the influence of echo chambers;

4. Enhance government transparency and trust: foster transparency in government communication by prioritizing clear and non-politicized messaging. The government should also explore partnerships with trusted individuals, organizations, and community

leaders to amplify accurate information and promote public confidence;

5.Continual research and evaluation: conduct further research to understand the relationship between echo chambers, psychological factors, and user behaviors specific to disinformation, particularly in the context of health-related disinformation in Thailand. This ongoing research will enable evidence-based decision-making and the refinement of interventions to address the evolving challenges of the infodemic.

By adopting this comprehensive approach, Thailand could proactively address the issue of echo chambers, strengthen resilience against disinformation, and foster a more informed public discourse surrounding COVID-19.

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