

Infodemic: Social Media and the Amplification of the COVID-19 Crisis in Canada

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Abstract

The COVID-19 pandemic will likely be remembered as profoundly transforming human relationships. Many people increased their use of social media during lockdown. Faced with the uncertainty of the situation, individuals turned to online interactions to better understand their reality. This has worsened a trend observed by researchers: the creation, spread, and reinforcement of fake news online. This misinformation not only created unfair competition with information from health authorities but also contributed to intensifying the crisis, reducing mitigation efforts, and affecting the resilience of populations (Mano, 2020). This study examines the impact of social media on exacerbating the COVID-19 crisis in Canada. Understanding this influence is crucial for evaluating the role of social media in handling health emergencies. We utilized network and content analysis techniques to illustrate that, beyond spreading fake news, an information warfare mentality drove the dissemination of disinformation during the pandemic. This dynamic significantly affected both collective and individual levels, particularly in shaping the knowledge system (a structured set of information used to detect or observe phenomena, translate them into perceived realities, and use these perceptions to make decisions) and influencing belief systems (orientations towards empirical data and other awareness) (Seitz et al., 2016). These findings suggest that the repercussions of this situation may endure within society.

Keywords

Social Media, Infodemic, Trust, Infox, SARF, Fake News, Disinformation, BERT, VADER

1. Introduction

For many months, the COVID-19 pandemic confined people to their homes. The

crisis increased the use of social media to stay in touch with loved ones, communicate, and obtain news in real-time. Thanks to social media, the circulation of information and data replaced that of people and viruses, which helped to relieve populations caught unprepared by the harshness of confinement and the limits on human contact. However, social media has been a double-edged sword, generating another type of virus (misinformation) and creating another pandemic (infodemic). In so doing, social media has plunged its users into doubt, causing them to reject scientific expertise and refuse to trust public authorities. Nevertheless, trust effectively reduces transaction costs in all social, economic, and political relationships. During the pandemic, the loss of this trust, manifested by wariness regarding messages from public health authorities in favour of urban legends and conspiracy theories circulating in social media, had a consequent impact. It has been proven that while social media is an incredible set of tools, it was not fully utilized during the COVID-19 pandemic crisis. This situation has occurred for over a decade, and Governments have increasingly incorporated social media into their e-governance (Banday & Matoo, 2013). This research underscores the urgent need for effective utilization of social media during health emergencies, inspiring us to harness its potential for the greater good.

This study is crucial in understanding how various disinformation networks contribute to spreading fake news through social media platforms during the COVID-19 pandemic in Canada. By employing content analysis, this article examines the channels of disinformation that lead to the rejection of institutional information by specific segments of the Canadian population during the pandemic. The findings of this study will significantly enhance our understanding of the construction of health belief systems by identifying the determinants of opinions and preferences in this area. The knowledge gained will provide valuable insights into anticipating barriers to persuasion by public service messages in this and many other related areas or situations, particularly in crises such as the COVID-19 pandemic. This understanding is crucial, and social media analysis can play a significant role in achieving it.

Recent changes to social media platforms' application programming interfaces (APIs) make it challenging to analyze social media because APIs are an accessible way of extracting and sharing data within and between platforms. The primary limitation of the X firehose and generous API call limits is the Boolean search and keyword dependence. In this article, the challenge is thoroughly addressed using COVID-19 data sets. One of the data sets is from the Borealis project, which is the Social Media Lab is a multi- and interdisciplinary research laboratory at Ted Rogers School of Management at Toronto Metropolitan University, which contains 237 million Tweet IDs for Twitter posts mentioning "COVID" between March and July 2020 (Gruzd & Mai, 2020). The other data set is from the Mega-COV project from the University of British Columbia (UBC), with almost 1 billion tweets, ensuring a comprehensive and reliable analysis.

The valuable information provided by public authorities plays a critical role in

responding to and recovering from a health crisis (Quinn, 2018). Effectively managing a health crisis requires public authorities to pinpoint the crisis's source, evaluate the situation, determine the causes, devise solutions, and offer credible assurances for a brighter and more secure future. However, the increasing use of social media has added complexity to this task. That new reality begs, therefore, the following research questions: To what extent has the dynamic of health-related information circulation on social media exacerbated the COVID-19 crisis by disregarding expert opinions and undermining trust in government institutions?

In seeking a response to that question, the following text presents a comprehensive exploration of the influence of social media on crisis management, focusing on the impact of the COVID-19 infodemic (Peng et al., 2018). It discusses various theories and frameworks, such as the Social Amplification of Risk Framework (SARF) and Attribution Theory, that aid in understanding the effects of misinformation on trust in health management information. The methodology and empirical findings, including network and content analysis, are also detailed in the article. Before that, this article summarizes and comments on the general situation of the COVID-19 crisis in Canada and then outlines the measures governments took to deal with the COVID-19 crisis in Canada.

2. Background: The General Situation of the COVID-19 Crisis in Canada

According to the Canadian Encyclopedia¹, as of July 2022, Canada has experienced seven distinct waves of the COVID-19 pandemic. The first wave peaked on May 30, 2020, leading to a subsequent decline in cases until late summer. Following this, the second wave began gaining momentum in mid-July 2020, sparking new restrictions, regional lockdowns, and expanded economic support measures by September 23. This wave reached its zenith in mid-January 2021 before gradually tapering off.

Subsequently, a third wave emerged in mid-March, reaching its peak in mid-April, which prompted the reinstatement of previously relaxed public health measures, especially in Alberta.

The fourth wave unfolded in the summer of 2021, resulting in renewed restrictions. This phase was characterized as a “pandemic of the unvaccinated” and peaked on September 26. Shortly after, a fifth wave swiftly developed in early November, driven by the spread of a more transmissible yet milder variant known as “Omicron.” The variant’s high transmissibility quickly strained laboratory testing capacities. By March 2022, it seemed that the fifth wave had peaked. However, by April 2022, public health officials in Canada declared the onset of a sixth wave and a seventh one in July of the same year (Detsky & Bogoch, 2022) see **Figure 1**.

In early July 2022, Quebec and Ontario reported the arrival of a seventh wave. Health experts have cautioned that COVID-19 cases may be underreported due to limitations in lab-based PCR testing and inconsistent data reporting. That ¹<https://www.thecanadianencyclopedia.ca/en/article/covid-19-pandemic> page accessed on August 6th, 2024.

information is consistent with the yearly report issued by the chief public officer of Canada^{2,3}. According to the latest account, as recorded in April 2024, Canada registered less than 5 million COVID cases for less than 60,000 deaths, with less than 3 million people recovering from their contagion to the virus⁴.

The COVID pandemic exposed several weaknesses in the Canadian healthcare system. It struggled to cope with the significant pressures on hospitals and health facilities. Simultaneously, the social system was severely impacted (Alami et al., 2021). This was evident as people were unable to bid a proper farewell to their loved ones who had died from the virus.

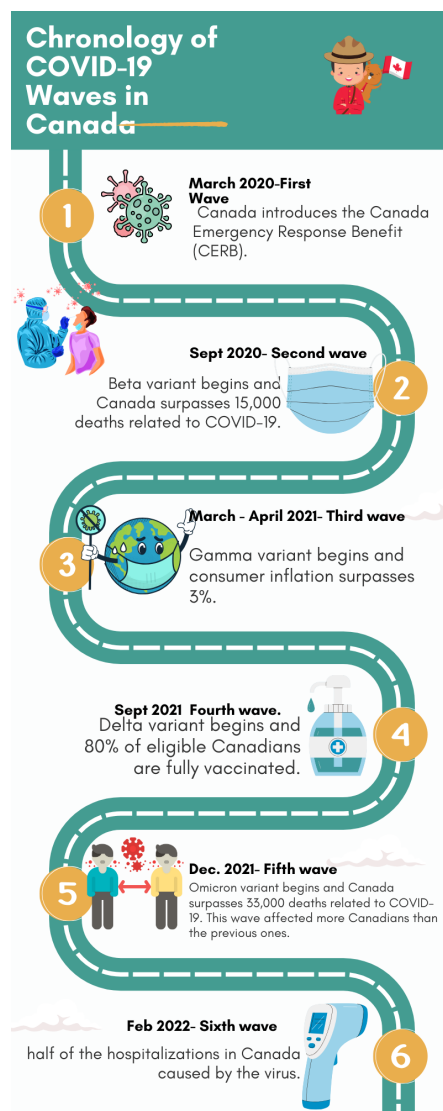


Figure 1. Chronology of COVID-19 waves in Canada.

²<https://www.canada.ca/content/dam/phac-aspc/documents/corporate/publications/chief-public-health-officer-reports-state-public-health-canada/state-public-health-canada-2022/report-rapport/report.pdf> page assessed on July 12th, 2024.

³Statistics Canada. Provisional Death Counts and Excess Mortality, January 2020 to April 2022. Statistics Canada; 2022.

⁴<https://www.worldometers.info/coronavirus/country/canada/> page assessed on August 5th, 2024.

The Government of Canada's Response to the Crisis

According to [McMahon et al. \(2020\)](#), the primary focus of the Canadian government during the pandemic has been safeguarding its citizens' health and safety. This has involved mobilizing the country's health research community to address the COVID-19 crisis. In coordinating these efforts, federal, provincial, and local governments have imposed various restrictions on the population, such as regulated movement, lockdowns, and the enforcement of public health measures like mask-wearing and mandatory vaccines.

The pandemic created a dire situation for many people who lost their jobs, became sick with COVID, were forced to quarantine, or became caregivers for someone affected by the virus. To help compensate for income losses and relieve the burden, the federal government created several wage subsidies for employees, self-employed individuals, employers, grants for community organizations and associations, and business loans.

In Canada, health is managed by provincial jurisdictions. During COVID-19, the federal government worked with provinces, territories, and collectivities to implement contact tracing and testing assistance, provide testing equipment, strengthen laboratory services, manage outbreaks, and provide voluntary, safe isolation sites. They also worked on vaccination administration IT programs.

The federal government also deployed numerous awareness resources to increase awareness and understanding of the disease, explain prevention and what to do if you develop symptoms, and address misinformation. This article is mainly concerned with the latter in assessing how some stakeholders reacted to the Government's effort on social media to manage the narrative during the Pandemic. The following section provides an overview of how social media are increasingly involved in managing crises.

3. Social Media and Crisis Management

During a crisis, social media increases the possibility of necessary dialogue between the authorities and the public ([Li et al., 2019](#)). The use of social media in crisis response and management is part of the field of crisis computing, a multidisciplinary field of study encompassing ongoing interactions and multimedia exchanges involving technology among individuals, organizations, and institutions during times of crisis ([Bukar et al., 2020](#)). [Palen et al. \(2007\)](#) defined crisis informatics as the empirical study, development, and deployment of information and communication technologies (ICTs) to manage crises ([Tonetto et al., 2023](#); [Gaspar et al., 2021](#)).

The integration of information technologies in general and social media, in particular, has made their use unavoidable during crises. Social media has become essential in organizing post-crisis assistance and coordinating the various organizations contributing to relief efforts. By providing adequate and real-time information to those the crisis has affected, social media allows individuals to understand the situation's full scope and report crisis managers' presence ([Reuter et al.,](#)

2017). Rapid, real-time delivery of information is undoubtedly one of the most widely used social media functions in times of crisis, potentially saving lives. In addition, it offers the advantage of reaching those cut off from traditional means of communication, particularly in developing countries where mobile phones are more common than landlines and access to smartphones and mobile devices is more common than desktop computers. Crisis informatics combines computer and social sciences (Palen & Anderson, 2016). Integrating IT technologies has facilitated the adoption and scale-up of crisis IT practices (Bukar et al., 2020).

Numerous organizations have incorporated social media into their crisis communication as part of their crisis prevention by growing their followers and increasing interaction before the crisis. Social media also contributes to crisis intervention and response by communicating with stakeholders and post-crisis messaging in real-time. Information gathered from social media is also part of the learning-from-experience process during the post-crisis stage.

Most common social media platforms have enabled a safe button that people use to let their relatives know they are safe. They also allow organizations to draft messages communicating critical information to help those in need. Social media also generates a great deal of data that organizations use to map out events or issues by delimitating their scope, communicating effectively, and reinforcing organizational resiliency. Now that the role of social media in a crisis is clarified let us see how it was used for disinformation during the Pandemic in the next section.

4. The COVID-19 Infodemic

The dissemination of misinformation regarding COVID-19 has proliferated extensively across social media platforms (van der Linden, 2022). This misinformation encompasses a diverse array of false assertions, from the promotion of spurious “remedies” such as lemon gargling, salt water gargling, and bleach injection (World Health Organization, 2020) and baseless conspiracy theories alleging that COVID-19 originated as a product of scientific experiments conducted in a Wuhan, China, laboratory (Andersen et al., 2020), to speculating that 5G cellular technology either causes or exacerbates COVID-19 symptoms. Research has shown that embracing conspiracy theories promoted on social media is associated with individuals disregarding government advice on social distancing and other public health interventions (Ahmad et al., 2020). Notably, the conspiratorial film *Plandemic*, which surfaced online on May 4, 2020, amassed millions of views, swiftly emerging as one of the most pervasive instances of COVID-19-related misinformation (Imhoff & Lamberty, 2020). This video propagates dangerous health misinformation, including the false assertion that wearing a mask can “activate” COVID-19. Furthermore, according to van der Linden et al. (2020), influential political figures such as former U.S. President Trump and Brazilian President Bolsonaro have actively perpetuated misinformation about COVID-19, erroneously asserting the efficacy of hydroxychloroquine as a treatment (Constine, 2020). However, misinformation about COVID-19 is not limited to obviously false

information, which complicates the problem. For example, although the disadvantages and benefits of hydroxychloroquine as a potential treatment are being investigated, there is currently no scientific consensus on its efficacy (Geleris et al., 2020). Therefore, determining what constitutes misinformation about COVID-19 is complicated because knowledge of the causes and treatments of the virus is evolving. However, as van der Linden et al. (2020) stated, misinformation about COVID-19 is a pervasive problem. In addition, according to the most viewed YouTube videos on COVID-19—more than 62 million views worldwide—more than 25% contained misleading information (Li et al., 2020). Lelisho et al. (2023) have also highlighted the negative impact of using social media during the pandemic with the increased panic amongst those getting their information through those platforms. For Cuello-Garcia et al. (2020), it is critical to master social media to better mitigate the impact of crises such as the COVID-19 pandemic because of the virulent effect of powerful social media influencers. At the same time, Al Banna et al. (2023) see the analysis of the big data generated by the increased use of social media during the pandemic through deep learning tools such as the Recurrent neural network (RNN) and the convolutional neural network (CNN) as a critical aspect in predicting the impact of COVID-19 on Mental health. Social media have been a great source of the propagation of conspiracy theories during the pandemic, significantly impacting people's decisions on health-protective behavior (Kouzy et al., 2020). The most reported conspiracies on social media include the following: the theory that the virus causing COVID-19 was created in a laboratory, the idea that COVID-19 symptoms are linked to 5G mobile network radiation, and the belief that certain pharmaceutical corporations and government agencies planned the pandemic (Allington et al., 2020; Clemente-Suárez et al., 2022). Concerning Canada, a study by Carleton University Professors found that nearly half of Canadians (46 percent) believed at least one of four COVID-19 conspiracy theories and myths addressed in the survey⁵. Some people who call themselves “coronavirus deniers” have used the hashtag #FilmYourHospital to urge others to visit nearby hospitals and take photos and videos. They are trying to prove their belief that the COVID-19 pandemic is fabricated and a hoax and that, indeed, the hospital was empty, thus demonstrating the conspiracy involving the media (Ahmed et al., 2020).

The Distrust of Institutional Sources of Information

Throughout the Pandemic in Canada, as elsewhere in the world, the distrust of institutional sources of information has increased. This is even one of the critical reasons for sharing unverified information on social media (van Zoonen et al., 2024). Trust can be defined as having positive expectations and being willing to become vulnerable (Mayer et al., 1995). It involves having positive expectations about others and being open to accepting vulnerability. When a person, group, or

⁵<https://newsroom.carleton.ca/2020/new-carleton-study-finds-covid-19-conspiracies-and-misinformation-spreading-online/>.

institution trusts, they can do so without constantly worrying or needing to monitor the other party's behavior (Levi & Stoker, 2000). Trust helps to reduce transaction costs in social, economic, and political relationships (Fukuyama, 1995). According to Ouattara et al. (2023), trust in politics is based on the relationship between the beliefs and preferences of the individual (citizens) and the qualities of the entity being trusted, such as an institution or a public figure. Political trust is a central indicator of the public's feelings about its polity (Newton & Norris, 2000). The key characteristics of trustworthiness are competence (the perception that someone can complete the desired task), benevolence (the perception that someone cares about my needs and will act in my best interests), and integrity (the belief that the person we are dealing with is honest and keeps their commitments) (Ozdemir & Sonmezay, 2020). This can apply to an individual or an institution. During the COVID-19 pandemic, some segments of the population engaged in disputes on social media regarding whether the Canadian government was displaying these three aspects of the way it was managing the crisis. The tendency to spread misinformation observed in certain groups during the COVID-19 pandemic in Canada is directly linked to trust (Di Domenico et al., 2021). It causes significant prejudice to institutions, especially during crises. What could be observed is that the crisis of trust on social media is mostly towards institutions because paradoxically, the trust (social trust) in online sources (individuals, friends, relatives, or group one belongs to) is also one of the main reasons of sharing false information online (Laato et al., 2020; van Zoonen et al., 2024). What transpired from the analysis of the distrust of institutions due to people sharing misinformation during the pandemic is the confirmation that social media is a challenging tool for institutional information (Bartlett et al., 2011; Olaniran & Williams, 2020). As a result, during a crisis, for example, people tend to share more non-institutional information than institutional information (Abedin & Babar, 2018). It is, therefore, critical for the Government to be perceived by its public as trustworthy, impartial, and transparent. That capital of image and sympathy needs to be built before the crisis since it has been observed that prior institutional trust significantly reduces exposure to online misinformation (Boulianne & Humprecht, 2023).

5. Theoretical Framework, Social Media, and Crisis Communication

Once the impact of social media on crisis management became clear, authors tried to understand how to use it in an unfolding contemporary crisis. Jin and Liu (2010) developed a blog-mediated crisis communication model, an innovative framework helping crisis management teams monitor and positively interact with influential bloggers during a crisis. In his literature review, Cheng (2018) explained how social media has transformed communication. Social media has thus shaped the content of organizations and stakeholders during the crisis by mixing visuals, texts, voice, and written messages. Social media crisis communication refers to using platforms such as Facebook, X (formerly Twitter), or Instagram to

manage and proactively respond to challenging situations or emergencies effectively. Its main objective is to quickly disseminate relevant information, respond to real-time concerns, and protect the reputations of individuals, organizations, or brands during a crisis (Wang et al., 2021). Interactive crisis management (ICM; Jin et al., 2007) was one of the first attempts to understand how user-generated content expresses emotions during a crisis. ICM highlights four primary emotions that crises trigger: anger, anxiety, fear, and sadness. These emotions are mapped on a matrix that considers the audience's coping strategies and the organization's level of involvement in crisis management. Additionally, social media allows end users to transform from passive receivers of an organization's messages during a crisis to active content generators producing data. Gaspar et al. (2016) conceptualized using such data to improve crisis management. In keeping with the logic of using social media data during a crisis, Kankanamge et al. (2019) discussed data collection through crowdsourcing, involving volunteers from the disaster field and other sectors such as marketing and communications. Saroj and Pal (2020) developed a set of theories associated with social media during natural disasters and catastrophe management. Social media crisis communication model of Austin et al. (2012) is paramount in contemporary crisis communication theory. Under this model, various social media audiences are in crisis, including influencers who generate information accessible to other users. Revised model of Hamid et al. (2023) emphasizes developing research-based insights on using social media in a crisis to apply it to various organizational domains.

Combining SARF with Attribution Theory

We will utilize theories of Love (2002) to underpin two concepts and frameworks better to comprehend our research question's social implications. SARF and attribution theory. Overall, Love's study is the most adapted conceptual approach is SARF, whose primary objective is to evaluate, interpret, and scrutinize the responses of both public and regulatory bodies to risk events (Kasperson et al., 2022). SARF is a holistic and multidisciplinary approach that analyzes how human perception and behaviour can contribute to amplifying or mitigating risk. It presents the crisis as the result of some critical amplifications, such as filtering signals with information accessible only to population segments, evaluating people's capacities to decode messages related to the crisis, and exploring how risk information is processed. SARF also analyzes behavioural changes in individuals and institutions. Key stakeholders act as amplification stations: scientists, risk management institutions, social channel platforms, activists, social organizations, opinion leaders, social groups, personal networks, and peer groups (Kasperson et al., 2022; Pidgeon et al., 2003). This approach corresponds precisely to the configuration of our research question and our evaluation of social media dynamics. Similar to our research, SARF considered social media as a critical amplification factor (Fellenor et al., 2020) because of its capacity to interfere with stakeholders' knowledge of an issue (cognition), their perception (connotative), and their attitude toward an issue. Social media thus shapes how people react to risk because it

allows them to share multiple signals, such as texts and videos. Researchers often use SARF to assess the perception of health-related risk issues. [Larson et al. \(2022\)](#) also discussed various aspects of the current COVID-19 vaccine experience. They stressed the importance of SARF and adjusted it appropriately to consider both the pervasive influence of social media and the systemic nature of the risk of vaccine hesitancy. This approach can significantly inform our understanding of this experience. Their conclusions highlight the potential of an adjusted application of SARF to structure descriptions and analysis of vaccine hesitancy. They also pointed out that SARF offers promising opportunities to guide concrete initiatives to improve the incidence and impact of vaccine hesitancy. The authors stated that the COVID-19 pandemic (the focus of our study) will provide new insights and information on risk communication practices in emergencies. [Zhang and Cozma \(2022\)](#) also pointed out that the dramatization and ambiguity of information in social media are prone to risk amplification. They suggested that SARF has probably been a valuable tool for informing health professionals about the true meaning of some observed social processes. This approach provides a solid foundation for understanding and managing infodemic issues in the COVID-19 context ([Wirz et al., 2018](#)).

The second component of our theoretical framework is attribution theory. [Weiner \(1986\)](#) developed attribution theory based on the assumption that individuals seek to understand the causes of events, mainly when they are unexpected and harmful. In applying attribution theory to the crisis context, the perception of responsibility or blame associated with that crisis largely determines its severity. Managers must, therefore, assess the situation to determine the best response to the crisis ([Coombs, 2007a](#); [Mowen, 1980](#)). In other words, understanding how individuals attribute responsibility for a crisis allows managers to anticipate reactions and choose the most appropriate actions to manage the crisis. This approach highlights the importance of the perception of responsibility in crisis management and the need for managers to consider these aspects when developing crisis response strategies. In a crisis like the COVID-19 pandemic, blame attribution is more straightforward to establish when the discourse can draw a causal link between an event and an organization ([Claeys & Cauberghe, 2015](#); [Nguyen et al., 2021](#)), as occurred on social media between some policy restrictions and people's growing discomfort. This is even more impactful when the attribution uses electronic word of mouth, as with social media, because it increases people's perception that such information is from an unbiased and trustworthy source ([Mata & Quesada, 2014](#)).

6. Methodology

Our approach merges quantitative and qualitative social media analysis, supported by insights from technology leveraging natural language processing (NLP) and deep machine learning, incorporating various linguistic tools ([Jaworska et al., 2024](#)). In this research, we investigate the influence of social media dynamics on the amplification of the COVID-19 crisis in Canada. Two key processes are essential

to achieve this: analyzing network interactions and examining social media content. We focus exclusively on X (formerly Twitter) for data analysis.

To analyze data on X, many researchers have used NodeXL, a network visualization tool that allows them to represent the relationships between X users and their interactions regarding specific content (Hansen et al., 2010; Smith et al., 2014; Smith et al., 2009). Every action on X leaves a footprint that helps build a network. NodeXL enables users to retrieve their X connection networks using the Clauset-Newman-Moore algorithm to segment network users into subgroups and generate graphs highlighting connections among them (Smith et al., 2014). The X communication platform offers great flexibility, allowing exchanges and word-to-word interactions with a wide range of users, even if they do not follow each other and are not part of the same network. X accounts can be public, accessible to all (including non-members), or accessible only to those in the user's network (Bruns & Liang, 2012; Bruns et al., 2012). Researchers collect data by tracking the evolution of keywords and tweets associated with these keywords. X offers two primary tools for accessing public tweets—the API and streaming—allowing you to view real-time tweets. There are three types of data analyses on X: business analysis, network analysis, and content analysis (Bruns & Liang, 2012).

The analysis of X activity involves the calculation of statistics and indicators describing this activity at a given time, based mainly on processing data sets from specific communication profiles. Additional data filtering may be required to understand better activity on X, such as assessing users or keywords. One can analyze activities on X on a temporal basis, including the overall volume of tweets and the hourly volume of different types of tweets over time (original tweets, replies, re-tweets, tweets with URLs). It is also based on the volume of specific keywords, the number of active users over a given period, and the average number of tweets per user. In addition, one can assess activity on X by comparing the activity of the most active users to those of infrequent users and by looking at the visibility of their tweets, as measured by the number of responses or retweets. The analysis of activity on X generally concludes with the evaluation of keywords and the most salient areas, according to Bruns and Liang's work (Bruns & Liang, 2012).

6.1. Data Capture

In 2023, most social media platforms, including X, TikTok, and Reddit, made significant adjustments to their API to increase revenue and find new ways to monetize their activities. Researchers have frequently leveraged APIs to gather large-scale data on social media users to understand organized online group behaviours. In this research, we stick to the analysis of X because we used the Mega-COV, a longitudinal, publicly available data set of 1.5 billion tweets in 104 languages that Professor Muhammad Abdul-Mageed and his team developed from March 2021 to March 2022 at the University of British Columbia (UBC) School of Information, UBC's Department of Linguistics, and Cornell University. We also cross-reference it with the Borealis project dataset. This time segment is critical to understanding how social media has amplified vaccine hesitancy and COVID-19

fatigue, triggering people to demonstrate and publicly contest government vaccine mandates and health experts' advice (Huang et al., 2022). We reported 1,157,986 tweets from the Mega-COV data set during that period.

6.2. Data Processing

Following Mackay et al. (2022) and Jaworska et al. (2024) and focusing their analysis on the role of influencers on social media, we have used three key aspects to identify COVID-19's stream of influence online in Canada during that period (see Figure 2) based on their level of engagement using the Muñoz-Expósito et al. (2017) equation:

$$\text{Engagement rate} = \frac{\text{Interaction tweet}}{\text{Reach of the tweet}} \text{Impression}_{\text{tweet}} \div X100$$

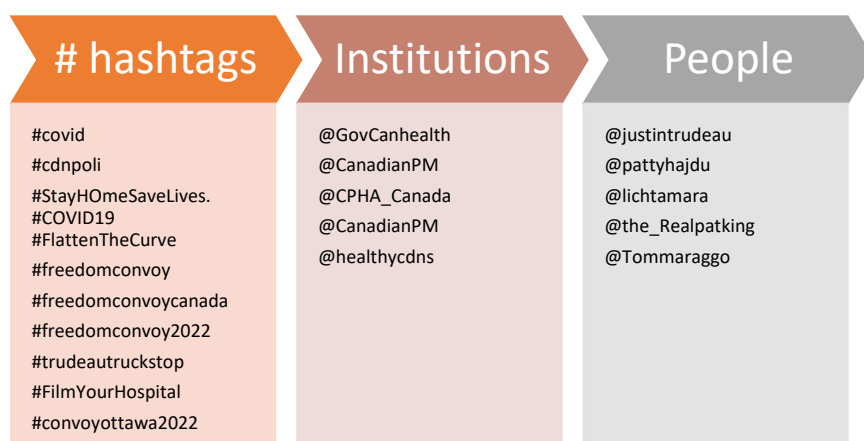


Figure 2. List of main influencers.

This reduced the number of tweets to 49,783. We have combined the average engagement rates of these accounts and hashtags on COVID-19 during that period (see Figure 3).

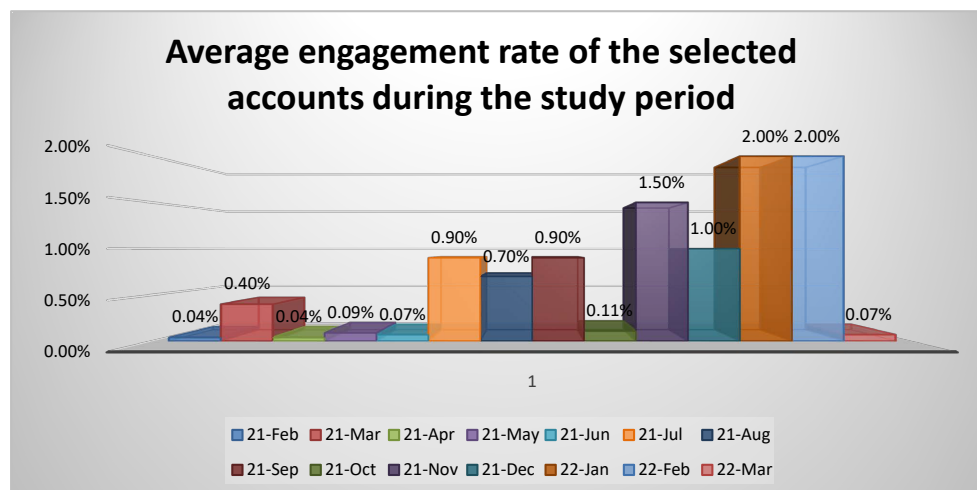


Figure 3. Average engagement rate of selected accounts.

6.3. Data Filtering: Context and Content-Based Extraction

Once we created the list of most common influencers, we extracted some features of the tweets using approach of [Anggrainingsih et al. \(2021\)](#) to discriminate tweets based on context and content. We did this through NLP matrix factorization for text modelling. On the one hand, for content-based filtration, we checked if the accounts (see [Figure 2](#)) were verified and had a description, content and URL, number of friends, followers, the average number of posts on a daily or weekly basis, and the level of engagement (see [Table 1](#)). On the other hand, we filtered the tweets based on their linguistic features such as the number of hashtags, word, and character length, tweet contents' URL, number of mentioned users, stock symbols, number of upper cases, exclamation marks, if they contained a multi such as “?” or “!”, number of emojis, number of words related to negatives or positive sentiments, number of pronouns, number of temporal references, lexical density, and if the content included slang or intensifiers. This process reduced the number of tweets to $n = 5807$, with 3474 tweets for the #freedomconvoy network and 2333 tweets for the #Stayhomesavelives network.

Table 1. The two networks' centralities.

Centrality Type	#StayHOMeSaveLives	#Freedomconvoy
Degree	3	2
Betweenness	4	3
Closeness	0.143	0.112
PageRank	0.238	0.129

6.4. Network Analysis

Data analysis on X is dual because it combines network analysis and content analysis ([Jiang et al., 2021](#)). We proceeded to the network analysis once we assigned the number of accounts and tweets. Network analysis determines a mapping of conversations on a topic by distinguishing network types from their division, density, and directorate ([Smith et al., 2014](#)). There are two types of network analysis: ego network analysis (ENA) and complete network analysis. For this research, we are more interested in the ENA, which assesses nodes' configuring relationships among network actors, revealing operative radius, node diameter, centrality, proximity, and interaction (betweenness) between nodes. This evaluation helps gauge the scope and influence of information circulating within the network. We can determine the network's nature using typology of [Smith et al. \(2014\)](#). The centrality of a node measures its prominence or structural importance in a network. A high centrality score may indicate power, influence, control, or status. Identifying the most central node allows information to be rapidly disseminated in a network, stop epidemics, protect against network breakdowns, and identify suspected terrorists. Network visualization measures various forms of centrality to identify the most influential nodes in a social network ([Samanta et al., 2021](#)).

PageRank, named after Google co-founder Larry Page, assesses the importance of nodes within a network. This metric is based on three key elements (see **Figure 4**):

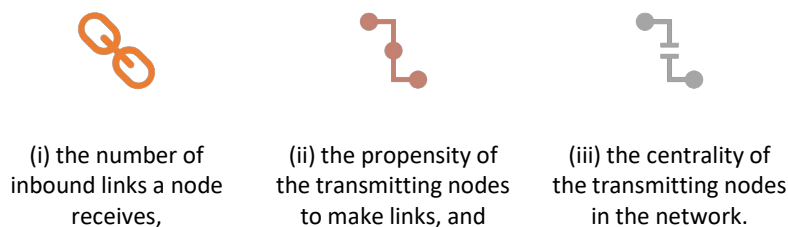


Figure 4. Key metrics assessing centrality of networks.

This comprehensive approach recognizes nodes’ crucial role and position in the network’s overall structure (Page, 1998). In this study, snow contracting and PageRank are both essential to assessing the influence of the different networks identified based on their centrality. The assessment shows two main networks based on online discussions around the hashtags #StayHOMeSaveLives (1) and #Freedomconvoy (2) (see **Figure 5**).

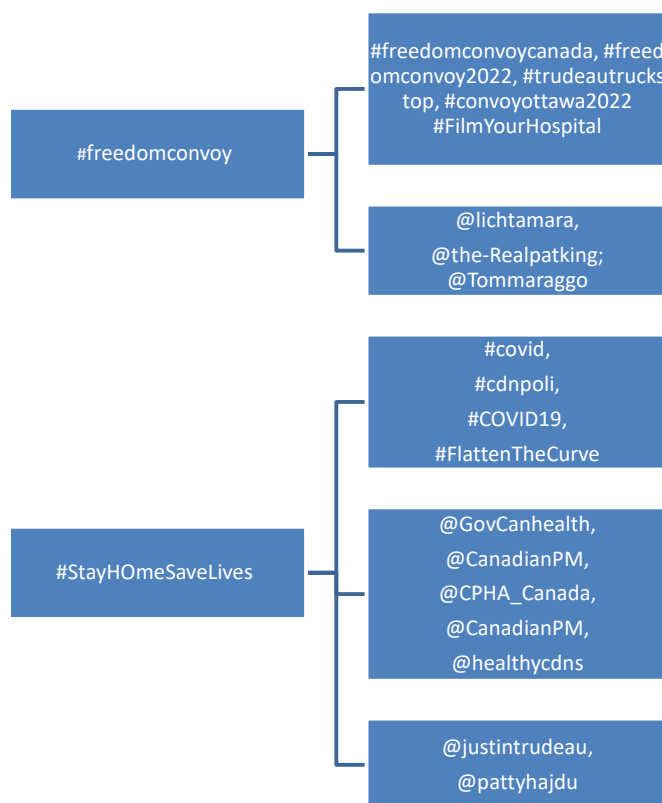


Figure 5. Network stakeholders repartition.

In social media analysis, we can measure the nodes’ dynamic using three leading indicators: degree, betweenness, and closeness (see **Table 1**).

6.5. Broadcasting to Mute

Initial observations suggest the existence of two distinct factions, each addressing the same topic but largely avoiding direct communication with one another. Instead, they interact through calls, tags, and frequent derogatory remarks, seemingly aimed at publicly denouncing political figures and media outlets in a naming-and-shaming strategy. Each of the two networks identified is formed from people and groups thinking alike, showcasing a great degree of homophily, which is the tendency to associate with people presenting similarities. Researchers have observed this in social media (de Zúñiga et al., 2022; Figeac & Favre, 2023). As Xu et al. (2022) explained in their “Arousal-Homophily-Echo” model, the homophily situation online fuels the arousal of complex emotions. In a crisis like COVID-19, homophily complexifies information management by blurring instructional messages and increasing selective exposition.

The other information the social graph of the two networks shows is the echo chamber effect (Terren & Borge Bravo, 2021) within each network. We used equation of Cinelli et al. (2021) to assess the echo chamber effect on both networks:

$$\mu_i = I_i I_i - 1 \sum_{j \in I_i} x_j.$$

The value of μ_i indicates the level of polarization among users reachable by a message that user i initially disseminates. The equation demonstrates the average inclination $h_{\mu}(x)_i$ of the influenced sets reached by users with a leaning of x across various data sets being considered (Cinelli et al., 2021). This portion evaluates the dissemination of misinformation within community networks utilizing the Susceptible-Infected-Retired methodology, as outlined in the epidemiological model of online information and fake news circulation (Kauk et al., 2021). The approach entails the following components: S for individuals prone to believing in misinformation; I for those infected who contemplate and distribute misinformation, indicated by their engagement level with such content; and R for individuals who verify information, reject misinformation, and halt its spread by refraining from sharing it further. The network analysis demonstrates a high level of polarization with agreement on the content of both networks. We evaluated the polarity of influencers using three leading indicators: number of followers, number of retweets, and number of mentions. We incorporated the Bidirectional Encoder Representation Transformer (BERT) into the data set of the two networks using the binary number with 0 for extreme anti-government measures and 1 for zealous pro-government measures. We obtained 91% of the cross-validated Area Under the Receiver Operating Characteristic curve, a commonly used metric for assessing binary classification and ideology polarization on social media (Jiang et al., 2021). This signals an increased level of political polarization. As Cornelson and Miloucheva (2022) demonstrated, political polarization during the COVID-19 pandemic has decreased trust and increased hostility along party lines, mainly regarding government-imposed vital measures such as social distancing and the mandated vaccine.

7. Content Analysis

In this article, we used a data mining perspective to establish a link between the circulation of misinformation, disinformation, fake news, and trust in institutional information. Theoretically, in this article, we draw on the concept of the trust economy that Laurent (2019) defined, as well as on approaches of Langlois et al. (2020) to information trust analysis to demonstrate that mischievous use (users) of social media and genuine consumption (content) coupled with the echo chambers phenomenon (Network) amplified the COVID-19-related crisis. Based on the homophily concept on social media (Figeac & Favre, 2023), we focus on the circulation of information within communities on social media in Canada during the study period (March 2021-March 2022) and the motivational factors that led to their propagation.

7.1. Opinion Mining

The opinion detection of the two networks has demonstrated key Canadian political and societal antagonistic debates displayed on social media during that time (see Figure 6). The main ones are the following:

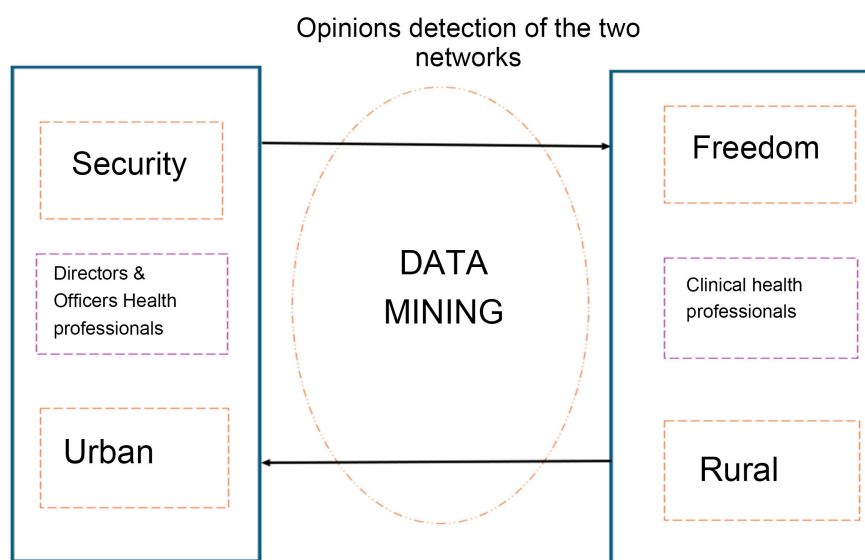


Figure 6. Opinion detection of the two networks.

- The existential and philosophical debate: Security versus freedom.
- The professional debate: Directors and officers health professionals versus clinical professionals.
- The geographical debate: Urban versus rural divide.

One of the main points of contention in social networks during the period we analyzed is the dichotomous debate between those who make freedom an absolute and inalienable value and right (the opinions expressed in the #freedomconvoy networks) and those who express a desire to ensure everyone's physical security (#stayhomesavelives). This is especially the case with the overrepresentation in

tweets of pronouns such as my, I, and me and the abundance of words such as deliverance, emancipation, liberation, and freedom associated with positive effects. The calls to action incorporate strong words and phrases such as fighting against subjugation, encumbrance, coercion, domestication, slavery, submission, freedom from the yoke, servitude, and tyranny, all associated with government measures such as mandated vaccines (61% of the cases; $n = 2119$), social distancing (18%; $n = 626$), wearing masks (14%; $n = 486$), and others (7%; $n = 243$), which are primarily found in the tweets of #freedomconvoy network. The overwhelming part of the vaccine is because that particular network becomes active in fighting against the vaccine.

The #stayhomesaveslives network had been functioning long before the #Freedomconvoy started. They presented themselves primarily as law-abiding citizens intensively using expressions such as

conscientious, decent, fair, forthright, genuine, honourable, impartial, reliable, sincere, straightforward, accurate, trustworthy, and virtuous, which are always associated with their actions toward government health measures. With 58% ($n = 1353$) of tweets from that network being from institutional accounts, the Federal government used intensively Twitter's account to disseminate messages about the Pandemic (Kada et al., 2022). The declination was more normative on how a lawful citizen is expected to act during such a crisis. As far as individuals are concerned, more than 11% ($n = 257$) of analyzed tweets expressed that even if they disagreed with governmental measures, they would still apply them to protect their loved ones and their communities.

The next debate displayed on the analyzed tweets was a professional one. Most health professionals with official responsibilities, whether a policymaker in the system such as chief public health officer (federal, provincial, cities) or those in charge in hospitals, were present and active on the #stayhomesaveslives network. In contrast, clinicians' health practitioners (those dealing directly with patients) were surprisingly underrepresented on that network. One might think doctors were too busy to be on social media during those crucial times. However, on the #freedomconvoy, tweets from American doctors such as Robert W. Malone (@RWMaloneMD), Peter McCullough (@P-McCulloughMD), Pierre Kory (@PierreKory), and Ryan Cole (@drcole12) were widely shared within the #freedomconvoy network. It is expected to think of members of the #freedomconvoy networks as radicals opposed to evidence-based policies. However, these well-articulated, renowned health professionals call for the readjustment of this assessment. Most were skeptical of the vaccine's efficacy and the political choice of medication and therapeutic response, using short videos to display knowledge and experience. They also demonstrate the gap in thinking during that crisis between clinical health professionals and those in charge of policy and managing the health system. Whatever the scientific truth in that situation, those messages have significantly interfered with the crisis management team's instructional messages. In crisis communication, instructional messages are critical because the crisis management team aims to provide clear,

concise instructions and information to help individuals understand and respond effectively during a crisis. Such messages guide actions and behaviours to ensure safety and reduce confusion (Shemberger, 2022; Sellnow et al., 2017). Because of homophily, there is no shared place where other doctors who think differently can respond to those American doctors' claims that the system has failed the citizens and corrupted health professionals for funding and professional gain. These messages not only feed the confirmation bias of the network members but are also a pivotal answer to the lingering attribution question people had: to whom do we owe this suffering? The tweets demonstrated that some members of that network had moved significantly through what Coombs (2007b) identified as three clusters of attribution: the victim cluster ("I cannot do anything about that"), the accidental cluster ("It is just bad luck"), and the preventable cluster ("The system is rigged, I have to do something about that to prevent further damage"). These three clusters trigger anger (Vignal Lambret & Barki, 2018). In such a crisis where one of the main arguments of the #stayhomesavelives network was naming and shaming members of the #freedomconvoy for not believing in science, the use of scientists such as the abovementioned American doctors could win over fence-sitters, increasing the anti-vaxxer base.

The third debate the content analysis pointed out is the divergence between people living in big cities and those living in campaigns⁶. There appears to be a geographical gap between people living in big cities, primarily members of the #stayhomesavelives network, and those living in the campaign #freedomconvoy network.

Politicians appear not to have considered the specificities of small towns in designing their one-size-fits-all policies with COVID-19 health measures. They have overlooked the terms "local realities," "provincial circumstances," "local context," and "the regional situation," which are often associated with ignorance, that are present in 8% ($n = 278$) of tweets from the #freedomconvoy network. For the #stayhomesavelives network, its members' rejection of particularities manifests in the attempt to promote a bandwagon effect by insisting on aligning with the rest and being an active agent in protecting themselves and their communities.

The latest aspect from the data set analysis is the absence of reference to any known fact-check resources such as AFP Factcheck (the Canadian arm of the global news agency digital verification service); even the posting referring to American content did not mention websites such as several useful fact-checking websites provide answers to political questions and evaluate the accuracy of claims made by politicians and news stories. These resources include *FactCheck*, which covers various topics, including science-based claims, healthcare debates, and social media news. Another helpful resource is *Politifact*, a non-profit organization

⁶The identification of account location on X is not automatic because people are free to choose whether to have their location identified or not in their settings. We made the localization identification on the profile when identified and on the content. Therefore, there is a higher risk of error in the estimation. We do not intend this section to explain that people in the campaign were against the government health measures, whereas those living in big cities were for them.

that fact-checks politicians, political parties, and news stories. Politifact also operates PunditFact, which fact-checks claims made by pundits, news writers, and celebrities. Additionally, *Snopes* uses evidence-based sources to assess news sources and social media posts, providing transparent ratings such as false, true, mixture, and unproven. *Lead Stories* is another fact-checking website that actively debunks false, deceptive, or inaccurate news and media circulating online. They are absent as reference points on the date set. This confirms the suspicious orientation around institutional information on social media, the abovementioned fact-checking organizations being considered to echo the institutional narrative.

7.2. Sentiments Analysis

Exploring social media content is invaluable due to its direct insights into the thoughts and emotions of users. However, interpreting the sentiment behind social media messages presents unique challenges due to their conciseness and potential for multiple interpretations. These messages must be better constructed and may exhibit language-related complexities such as diverse vocabulary, spelling errors, and unconventional syntax. Social media content, especially concerning urgent topics like the COVID-19 pandemic, undergoes rapid transformation due to varying perspectives, trending topics, and user interactions. Furthermore, users share content and personal characteristics such as gender, location, and age, which can significantly impact sentiment analysis. Sentiment analysis models must factor in the linguistic diversity of social networks, where less than half of the messages are in English. Consequently, social networks introduce new challenges and opportunities for sentiment analysis owing to their rich content and intricate relationships. Understanding these challenges and opportunities is crucial for practical sentiment analysis (Fersini, 2017).

Emotions in a crisis are significant and can significantly impact its progression. The judgment of how political leaders react to a crisis depends on the emotions influencing the propensity to trust the authorities during the crisis (Kaur et al., 2021). However, in this research, we are interested in knowing how social media contributed to amplifying the crisis during the period analyzed in Canada. We used the Valence Aware Dictionary and Sentiment Reasoner (VADER), a rule-based sentiment analysis tool and lexicon for the sentiment analysis. In identifying sentiment in the data sets, VADER first breaches each text in individual words to assess if it is positive or negative, neutral or compounded.

- Positive sentiment: compound value > 0.001, assign score = 1.
- Neutral sentiment: (compound value > -0.001).
- (compound value < 0.001), assign score = 0.
- Negative sentiment: compound value < -0.001, assign score = -1 (Çilgin et al., 2022).

Adapted to the #Freedomconvoy, VADER has displayed a set of emotions (see **Figure 7**):

Almost 85% ($n = 12$) of emotions expressed in the #Freedomconvoy networks

are classified as negative, with about 1% ($n = 1.5$) as positive. Researchers showed that the COVID-19 crisis hugely impacted mental health (Crocamo et al., 2021; Valdez et al., 2020; Odriozola-González et al., 2020). Specifically, researchers such as Liu et al. (2020) and Geirdal et al. (2021) investigated social media's harmful effect on users' perceived well-being during COVID-19. In this case, we can draw a link between the exposure to X's messages, the reinforcement of these messages through trusted sources (for network members), and their emotional response. Bendau et al. (2021) found a correlation between seeking information online about COVID-19 and increasing anxiety in some people. Although the emotions trends analysis cannot establish a direct link between information seekers on the #freedomeconvoy network, the reported increased emotion impacted the crisis amplification and their distrust of information from authorities. As Coombs and Tachkova (2023) demonstrated, emotion-oriented processing is crucial in crisis communication because it not only triggers intense responses from stakeholders, such as reprisals, boycotting, or other punitive measures, but also shapes the cognitive processing of crisis information, mainly in terms of how individuals perceive the crisis and the organization involved.

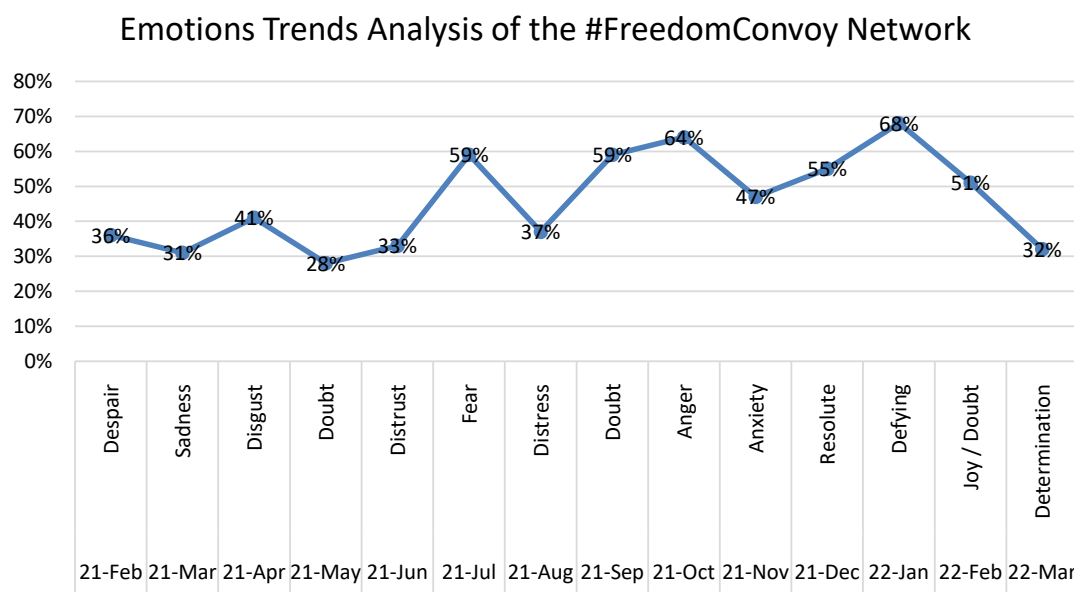


Figure 7. Emotions trends analysis of the #Freedomconvoy network.

In the mentioned network, there is a focus on perceived self-efficacy (van Zonnen et al., 2024). More than 67% ($n = 10$) of posts in the #freedomconvoy network encourage people not to be naive or gullible and to question obvious information. While these studies did not create a specific tool to assess user psychology, the prevalent use of key terms and words in the dataset, such as audacity, rudeness, and impudence, provides insight into a common trait that emerged from the analyzed exchanges: overconfidence (Borgholthaus et al., 2023). This overconfidence makes users overestimate their ability to detect misinformation and spread

false narratives (Serra-Garcia & Gneezy, 2021). Overconfidence involves individuals overestimating their skills and consists of two main components: the “better-than-average” effect and the “miscalibration” effect. The “better-than-average” effect leads overconfident individuals to believe that their skills and abilities surpass those of the average person. In contrast, the “miscalibration” effect gives individuals unwarranted certainty about a prediction despite the surrounding environmental conditions (Borgholthaus et al., 2023). The Better-than-average Effect (BTAE) is evident in the data set through terms representing awareness, the rejection of idleness, and expressions related to disbelief, caution, skepticism, and wariness. Multiple calls for wakefulness, cheekiness, and inquisitiveness about various issues on the dataset demonstrate the BTAE attitude. This attitude is visible primarily throughout the hashtag analysis of the #FilmYourHospital, where people are empowered to find evidence of foul plays and setups related to the pandemic in nearby hospitals. The other trend observed in the datasets is the temptation of playing the journalist by being the person who breaks the news to other members of their network. This is consistent with findings from Gerts et al. (2021). People eager to share information rarely take the time to check its accuracy or key factual aspects. Consequently, tweets with false information show a more significant negative sentiment than those without misinformation. The timestamping analysis of the #FreedomConvoy Network data and the sequence of events shows that 89% ($n = 3092$) of tweets were shared within the 3 minutes of their reception.

8. Conclusion

Social media is transforming crisis management. Social media is seen as a tool that gives a voice to marginalized groups by lowering the cost of participating in public discussions. However, this research shows that it can also harm civic engagement and erode trust in institutional messages, particularly during times of crisis. In this study, we demonstrated that the impact of orchestrated misinformation, particularly evident during the COVID-19 pandemic, extends far beyond disseminating fake news. We delved into the realm of information warfare aimed at influencing not only individuals’ knowledge systems but also their belief systems. Belief systems encompass explicit and implicit orientations toward empirical data and other forms of knowledge or consciousness. They incorporate the unconscious and subconscious elements, which can wield considerable influence without the individual’s awareness. Belief systems are profoundly personal and may vary significantly from one individual to another because of these subconscious elements. Knowledge systems are structured frameworks that perceive and interpret observable indicators or designators, translating them into perceived realities that inform decision-making and action. Knowledge systems operate on scientific principles, which the scientific method supports. Essentially, researchers gather empirical data through observation or detection, formulate hypotheses, conduct tests to validate or refute these hypotheses, and employ the results to guide further action. During COVID-19, social media impacted cognition (how people acquire information

and what information they expose themselves to) and attitude (how they felt about the crisis). By defying apathy, social media has contributed to amplifying the crisis by increasing distrust of institutional sources of information and thus diminishing the response and recovery impact of the crisis management process.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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