

**Public Health Emergencies and Public Opinion on Social Media:
A Framing and Network Agenda-Setting Study of COVID-19**

**A Dissertation Presented for the
Doctor of Philosophy
Degree
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**Iman Tahamtan
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DEDICATION

To my parents, Khalil and Soheila Tahamtan, for believing in me and supporting me both financially and emotionally.

To my spouse, Rose Tahamtan, for her support, motivation, encouragement, patience, dedication, and love.

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ABSTRACT

The COVID-19 pandemic was a public health crisis that started in March 2020, leading to a global quarantine, motivating millions of people worldwide to share billions of information about various aspects of the disease on social media. Studying public opinion on social media can identify the perspectives, feelings, needs and preferences of citizens, and guide governments and authorities to make better policies and decisions during any public crisis. Although a few recent studies have analyzed social media data about COVID-19, public opinion about the pandemic remains understudied. To fill this gap in the literature, this study used framing theory, thematic analysis, data analytics, and text mining to analyze trending hashtags about COVID-19 in the US, and hashtags associated with them, along with the 694,582 tweets containing those hashtags in March 2020 to (1) identify how the public framed their opinion about COVID-19 during the initial weeks of the pandemic, using hashtags, and (2) determine the frames that received more public engagement and adoption on Twitter. Additionally, this study used content analysis (3) to identify the WHO agenda on Twitter about the pandemic, and utilized the network agenda-setting model, text mining, quadratic assignment procedure and Granger causality to (4) examine the relationship between the World Health Organization's (WHO) agenda on Twitter and the agenda of 7.5 million of its followers on Twitter regarding the COVID-19 pandemic, particularly 6 Twitter user categories, including healthcare professionals, academics, politicians, print and electronic media, legal professionals, and the private sector. The thematic analysis identified 9 frames in public opinion on Twitter including "public health guidelines," "quarantine life," "solidarity," "evidence and facts," "call for action," "politics," "post-pandemic life," "shortage panic," and "conflict." This study indicated that the frequency of a frame on social media does not necessarily mean greater public engagement with the frame or adoption of it. This study informs the framing theory by showing that frames and the themes

related to them represent the consequences of the COVID-19 pandemic, and trending hashtags are appropriate tools to use in the framing analysis of social media data. This study provides data-driven evidence that governments, practitioners, organizations, activists, and authorities can use hashtags to effectively communicate health messages to people during public health emergencies. Additionally, the content analysis revealed 7 topics that reflected the WHO agenda about the pandemic, including “prevention,” “solidarity,” “charity,” “teamwork,” “ill-effect,” “surveillance,” and “credibility.” A significant and strong correlation was found between the WHO agenda network and the agenda network of the 6 Twitter user categories. This study contributes to the agenda-setting theory by providing evidence that agenda-setting effects vary by Twitter user category and issue type, and that there can be “two-way” or “multiway” agenda-setting effects on social media, where various categories of social media users influence each other’s agenda.

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CHAPTER 1: INTRODUCTION

Public Opinion on Social Media

Governments, public health organizations, and health authorities need to make appropriate and prompt decisions to manage and control public crises such as the COVID-19 pandemic (Wang et al., 2020). During the COVID-19 pandemic, in order to make appropriate decisions and policies, some scholars and authorities proposed that public opinion should be regularly monitor and analyzed (Wang et al., 2020) because it reflects the needs, feelings, concerns, and preferences of citizens. For instance, the Taiwan Public Opinion Foundation survey in mid-February 2020 indicated that the Taiwan government received a high approval rate by the public for handling the covid-19 crisis (Wang et al., 2020).

An effective approach to learn about public opinion, in addition to surveys and interviews, is to analyze people's conversations on social media (Chew & Eysenbach, 2010). The insights produced from the big data analysis of social media can be a valuable source of information for public health surveillance and scientific discovery (Vydiswaran et al., 2014). Governments and health authorities can use such insights to take appropriate actions during health emergencies (Chew & Eysenbach, 2010). For instance, social media data can be used to track the local and global outbreaks of diseases (Cassa et al., 2013) or the changes in people's opinions about any health issue over time (Chew & Eysenbach, 2010). The analysis of social media data can also be used to study how health information is presented to people, how people learn and discuss various issues related to a health crisis, how engaged people are in those issues (Moy & Bosch, 2013), and how people collectively cope with a global pandemic like COVID-19 (Ferrara, 2020). Another advantage of analyzing public opinion on social media is that it can result in discovering issues that require further investigation through subgroup analysis, surveys, interviews, or interventions (Kim et al., 2017).

Twitter and Hashtags

Twitter is a social networking site launched in 2006, that has been extensively used to learn more about public opinion on topics such as political debates, social issues, and health crises. Twitter facilitates communication worldwide and provides people with the opportunity to share their views and feelings on different issues (Robinson-Garcia et al., 2017).

On Twitter, hashtags, the user-generated metadata, were initially used to organize and search for information and connect people with similar interests to relevant online topics and communities (Potnis & Tahamtan, 2021). Hashtags on Twitter are extensively used to mobilize social and political movements (DeMasi et al., 2016). Hashtags can also be used to disseminate information and bring people's attention to various public health, environmental, economic, social, and political issues (see e.g., Enli & Simonsen, 2018; Karami et al., 2018; Recuero et al., 2015). Hashtags have information and communicative power, that if used appropriately, can initiate a public debate and establish an agenda in society (Veletsianos, 2017).

Problem Statement

The unfolding of the COVID-19 pandemic resulted in the spread of billions of information on social media by the public, organizations, governmental officials, healthcare professionals, politicians, and journalists (Hammer et al., 2021; WHO et al., 2021). The high volume of information produced on social media can be used to analyze and understand how people communicated with each other and framed their opinion about the COVID-19 pandemic, particularly during the initial weeks of the pandemic. Analyzing social media data can also provide insights into how successful organizations such as the World Health Organization (WHO) are in transferring their COVID-19 agenda to the public.

Despite a few recent studies that have analyzed social media data concerning the COVID-19 crisis (Han et al., 2020; Wicke & Bolognesi, 2020), public opinion about the pandemic is still not well studied. The primary goal of this dissertation is to extend the state of the art in this area by pursuing the following objectives:

(1) identify how the public framed their opinion about COVID-19, using hashtag, during the initial weeks of the pandemic, and (2) determine the frames that received more public engagement and adoption on Twitter. Framing theory, thematic analysis, and data analytics were used to address these objectives in chapter 2 of this dissertation.

(3) to identify the WHO agenda on Twitter about the pandemic, and (4) examine the relationship between the WHO agenda and the agenda of 7.5 million of its followers on Twitter regarding the COVID-19 pandemic, particularly 6 Twitter user categories, including healthcare professionals, academics, politicians, print and electronic media, legal professionals, and the private sector. The network agenda-setting model, content analysis, text mining, and several statistical tests were used to address these objectives in chapter 3 of the dissertation.

Overview of Chapters

The main body of this dissertation consists of 2 chapters that analyze public opinion and the WHO agenda on Twitter about the COVID-19 pandemic. Chapter 4 provides a summary of the conclusions and contributions resulting from this work. A brief description of chapters 2 and 3 is presented in the following sections.

Overview of Chapter 2

Framing research has been mostly focused on how the news media frame various issues and present them to the public, as well as their impact on public opinion (Nisbet, 2010). The literature indicates that how the news media frame public issues can impact public opinion (H. De Vreese, 2001), consequently impacting

how the public understands those issues and frames its opinion about them. However, the emergence of social media has allowed people to communicate with each other and develop their own frames, independent of the news media. As a result, most public issues primarily gain attention on social media while being absent in the news media (Rogstad, 2016; Van Gorp, 2010). People often frame their opinion through personal experiences and conversations with others, by adopting the frames in the news media or other sources, or by using terms that are familiar to them (Nisbet, 2010).

The study presented in chapter 2 is different from past framing studies and contributes to the literature in several ways. First, almost all past studies have examined the frames in the news media about COVID-19 (Benziman, 2020; Ogbodo et al., 2020; Park et al., 2020; Poirier et al., 2020; Yu et al., 2020), while chapter 2 analyzes the frames in public opinion about the COVID-19 pandemic on Twitter. Second, unlike previous studies, chapter 2 investigates which frames in public opinion have received greater public attention on Twitter. Third, this study demonstrates how (trending) hashtags, as user-generated metadata, can be used in framing analysis of social media data during public crises.

Overview of Chapter 3

Following the COVID-19 pandemic in early 2020, the world entered a global crisis that made compliance with public health guidelines more critical than ever. The information overload and spread of wrong information about COVID-19 on social media made the distribution of reliable public health information with the world vital (WHO et al., 2021). Public health organizations like WHO, that is an important source of health information for most people worldwide, used its Twitter account to communicate various issues about the pandemic to the public. To date, few to no studies have examined the agenda-setting effect of WHO on public opinion during a global pandemic. To fill this gap in the literature, this study took the first

step by questioning how the issues related to COVID-19 communicated by WHO to the public on Twitter, constituting the WHO agenda about the pandemic, influenced public opinion on Twitter.

The agenda-setting theory, particularly the network agenda-setting model, was used address to the questions proposed in chapter 3. The network agenda-setting model asserts that the news media can impact public agenda by making networked issues salient in people's minds (Chen et al., 2019). Most agenda-setting studies are centered around the agenda-setting effect of the news media, particularly in the context of political debates.

Chapter 3 enhances our knowledge of the network agenda-setting effect of public health organizations, namely WHO, on public agenda. Chapter 3 also discusses how different Twitter user categories like academics versus healthcare professionals may react differently to the agenda set by WHO on Twitter. Chapter 3 suggests that WHO can use social media and hashtags to more effectively impact public opinion next time a public health emergency emerges.

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CHAPTER 2: FRAMING OF AND ATTENTION TO COVID-19 ON TWITTER: THEMATIC ANALYSIS OF HASHTAGS

A version of this chapter was originally published by Tahamtan et al. (2021):

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ABSTRACT

Although several past studies have addressed how the news media have framed the COVID-19 pandemic, they may not accurately capture and represent the perspectives of the public about the pandemic. This study identifies how the public framed their opinion about the COVID-19 pandemic on Twitter, using hashtags, during the initial weeks of the pandemic, and what frames received greater public attention. This study collected and analyzed 22 trending hashtags about the pandemic in the US and other hashtags associated with them in March 2020, along with the 694,582 tweets written in English containing those hashtags. Public attention to the frames was measured by evaluating the amount of public engagement with frames and public adoption of frames. The thematic analysis identified 9 frames including “public health guidelines,” “quarantine life,” “solidarity,” “evidence and facts,” “call for action,” “politics,” “post-pandemic life,” “shortage panic,” and “conflict.” The results showed that frames such as “call for action” were more appealing than others, receiving greater public adoption and engagement. This frame had the highest public engagement score, followed by “conflict” and “evidence and facts”. Additionally, “post-pandemic life” had the highest adoption score, followed by “call for action” and “shortage panic”. This study indicated that the frequency of a frame on social media does not necessarily mean greater public engagement with the frame or adoption of it. This study contributes to the framing theory and research by demonstrating how hashtags, as user-generated metadata, can be used for framing analysis of social media data. This study concludes that the identified frames about the COVID-19 pandemic, such as “quarantine life” and “conflict” and their subthemes such as “isolation” and “toilet paper panic” represent the consequences of the COVID-19 pandemic. The consequences could be (a) exclusively related to COVID-19, such as hand hygiene or isolation, (b) related to

any health crisis such as social support of vulnerable groups, or (c) generic, that are irrespective of COVID-19, such as homeschooling or remote working.

INTRODUCTION

Public Opinion about COVID-19 on Twitter

COVID-19 is a global public health pandemic threatening millions of lives worldwide, leading to approximately 188,655,968 confirmed cases and 4,067,517 deaths across the globe as of July 16, 2021 (WHO, 2021). Twitter was used as a main platform for information and knowledge dissemination about the pandemic, resulting in generating massive data about various aspects of the virus (Merchant & Lurie, 2020). Twitter has become the most frequently used communication medium for disseminating health information since the outbreak of H1N1 in 2009 (Chew & Eysenbach, 2010) and later during the outbreak of the H7N9 virus, or bird flu, in 2013 (Vos & Buckner, 2016). It was also a platform for discussing the Zika virus epidemic in 2015 and 2016 (Fu et al., 2016).

People use Twitter and other social media platforms to interact with each other, share their opinion, and engage with the messages generated by others in real time. Twitter also allows public health gatekeepers to interact with the public directly. For instance, the Centers for Disease Control and Prevention (CDC), WHO, health care officials, and other organizations used Twitter regularly to share health messages about the COVID-19 pandemic and communicate its risks to the public (Merchant & Lurie, 2020).

The data shared on Twitter can be used to analyze and gain a better understanding of public opinion, which could help identify the needs, concerns, priorities, and preferences of people in real time. This could in turn impact public policy by encouraging governments and healthcare officials to distribute proper resources, act, and plan accordingly (Burstein, 2003; Han et al., 2020; Page & Shapiro, 1983). For instance, Avery (2017) reported that monitoring public opinion about the Zika virus crisis on social media helped public information officers have a higher level of preparedness for managing the crisis.

Framing Analysis of Public Opinion

Public opinion refers to people's collective opinion about an issue such as COVID-19. The public consists of all the groups and subgroups in society, such as workers, doctors, officials, politicians, journalists, and students (Hannay, 2005). An effective strategy to understanding public opinion and attention to an issue is analyzing how people perceive and frame the issue (Goffman, 1974; Neuman et al., 2014).

The framing theory is used as a framework in this study to analyze public opinion. Framing refers to selecting some aspects of an issue, promoting them, and making them salient (Entman, 1993). Journalists and the news media often use framing to conceptualize an issue, bring public attention to some aspects of it, and minimize attention to other aspects of it (Chong & Druckman, 2007b; Shih et al., 2008). People also use framing to make sense of complex issues, interpret and organize them into comprehensible concepts, and present them to others (Kaufman et al., 2003).

Framing analysis of public opinion provides valuable insights into the content and sentiment-based aspects of an issue (Meraz & Papacharissi, 2013). Frames can serve as a starting point for designing effective messages to address people's needs and concerns during public health crises (Park et al., 2020). Journalists, policymakers, professionals, and scientists use frames to communicate their messages in a more effective way that is more easily understandable by the public (Van Gorp, 2010). Framing can also be used by governments, advocacy groups, and authorities to design public education materials, present more engaging and effective public dialogue, write more relevant stories for the public, and expand their audience, reach and impact (Nisbet, 2010). For instance, framing of messages related to COVID-19 can be used to design and target messages in an effective way to enhance public engagement with and adoption of public health guidelines (Wicke & Bolognesi, 2020).

Effect of Frames on Public Attention

An important aspect of framing research is to study the effect of frames on public attention. “Public attention refers to the general acknowledgement of a subject in the public sphere and subsequent civic discourse on the subject” (Stoltz & Taylor, 2017, p. 31). Different frames about an issue can cause various effects on public attention. A small change in how a topic is presented can sometimes cause a butterfly effect on public attention (Chong & Druckman, 2007b). Framing or reframing an issue can shift how people understand the story, consequently changing how people respond to it (Kaufman et al., 2003). Once the public turns its attention towards a series of frames about an issue and adopts those frames, it is likely that they collectively agree on the best decision and course of action (Chong & Druckman, 2007b). The study by Krishnamurthy et al. (2001) showed that when discussing the performance of medical treatments, the messages framed positively (i.e., the chance of treatment success rather than its failure) had a greater impact on health treatment decisions. Almashat et al. (2008) indicated that survival frames (i.e., the likelihood of surviving a certain procedure) would lead to making more informed medical decisions than mortality frames (i.e., the possibility of dying from a certain procedure). Analyzing the effect of COVID-19 frames on public attention can lead to determining which frames are more effective in receiving greater attention and impacting public opinion.

In summary, Twitter provides valuable user-generated data that can be beneficial for different stakeholders to respond to health crises. Although some studies have analyzed the frames about COVID-19 with a focus on the news media of politicians (Benziman, 2020; Ogbodo et al., 2020; Park et al., 2020; Poirier et al., 2020; Yu et al., 2020), there is no systematic study about how people frame their opinion about COVID-19 on Twitter. Therefore, this study tries to fill this gap with the following research objectives.

Research objectives

The aim of this research was to (1) identify how the public framed their opinion about COVID-19 on Twitter, using hashtags, during the initial weeks of the pandemic and (2) analyze which frames received greater public attention on Twitter.

LITERATURE REVIEW

Framing of the COVID-19 Pandemic

During public health emergencies, it is critical to communicate public health messages and guidelines to the public effectively. One way to make public health messages more effective is to frame them in a way that helps people understand health crises and to impact their decision-making and actions. Previous empirical research shows that the news media play an important role in framing public health issues (Yu et al., 2020). As Table 1 shows, Ogbodo et al. (2020) analyzed the frames in 8 leading global media outlets, such as the BBC, News York Times, CNN, and People's Daily. Poirier et al. (2020) investigated the frames used in the front pages of 12 well-known Canadian news media sources. Park et al. (2020) analyzed Korean COVID-19-related tweets to identify medical and non-medical frames in the news, and Yu et al. (2020) studied the frames in the tweets of 2 major newspapers in Spain.

The literature on the framing of COVID-19 shows that most past studies have focused on how political figures and the news media have framed the COVID-19 pandemic (Benziman, 2020). These studies reflect the frames promoted by established gatekeepers in society who often have some hidden agenda. Unlike past framing studies, this study focuses on the frames related to COVID-19 in public opinion on Twitter, which voices the perspectives of diverse groups of people.

Hashtags for Framing Messages on Twitter

Framing research uses the linguistic features of communicating text to identify frames, including headlines or subheads of newspapers; photographs and photo captions; paragraphs of articles (Reese et al., 2001); social media posts, such as tweets (Moy & Bosch, 2013); and other visual images, like icons (Gamson & Modigliani, 1989). For instance, Hellmueller and Zhang (2019) used photographs to identify frames regarding the European refugee crisis in CNN International and Der Spiegel online news sites, or Benziman (2020) used the US President and British Prime Minister speeches to identify how they framed issues related to COVID-19.

The current study proposes that hashtags are a linguistic feature that can be used to identify frames on Twitter and other social media platforms. Hashtags serve as catchphrases that can be used to identify frames in tweets (Hemphill et al., 2013). They represent a shared meaning or context (Lehmann et al., 2012) that, similar to frames, can highlight the most salient aspects of an issue (see Rodriguez & Dimitrova, 2011) in such a way to promote it (see Entman, 1993).

In circumstances such as breaking or emerging events, a specific hashtag (e.g., #BlackLivesMatter) or a set of hashtags (e.g., #StayHome, #WashYourHands) become the main channel to represent an issue in online conversations by social media users. Hashtags that gain community-wide adoption and popularity can be used to identify the ad hoc framing of an event. Widely adopted hashtags show how the public frames a topic and can be used to determine the thematic frames of the issue (Meraz & Papacharissi, 2013). Nevertheless, limited studies have acknowledged the possibility of using hashtags to identify frames (e.g., Hemphill et al., 2013; Meraz & Papacharissi, 2013). Hence, this study utilizes hashtags in framing analysis of social media data, a new approach that has been rarely explored in previous studies.

Table 1. Framing of COVID-19 by the news media.

#	Study population	Key findings of past research	Source
1	Global media outlets, such as <i>BBC, News York Times, CNN, and People's Daily</i> .	(a) Human interest: refers to framing messages in a way to personalize and dramatize news to attract greater audience interest (Semetko & Valkenburg, 2000), (b) Fear/scaremongering: framing messages in an exaggerated way to cause fear or panic in the public (Ogbodo et al., 2020).	Ogbodo et al. (2020)
2	Front pages of 12 well-known Canadian news media sources	(a) Health crisis: the most dominant frame, (b) Chinese outbreak, (c) Economic crisis, (d) Helping Canadians, (e) Social impact, (f) Western deterioration (Poirier et al., 2020).	Poirier et al. (2020)

Table 1. Continued.

#	Study population	Key findings of past research	Source
3	Tweets of Korean news media	Medical frames: health issues related to COVID-19. Non-medical frames: (a) Conflict: disagreements about COVID-19, (b) Human interest: the positive role of people in handling COVID-19, (c) Attribution of responsibility: government and public officials are responsible for the crisis, (d) Morality: moral and ethical messages (Park et al., 2020).	Park et al. (2020)
4	Spanish newspapers	(a) Livelihood: family life and children, (b) Public health professional: news about the department of public health, (c) Pandemic update: contagion and death toll, (d) Politics: general political news, (e) State of alarm: government's announcement and policy update, (f) Economy: the effect of the pandemic on the Spanish economy, (g) COVID information: general information about the pandemic, (h) Lockdown, (i) Hospital (Yu et al., 2020, p. 4).	Yu et al. (2020)

Trending Hashtags in Frame Analysis

Among the numerous widely adopted hashtags on social media, some may become trendy and viral. Popular hashtags emerge in response to breaking news and other unexpected events, such as when an important, nationwide, or global issue happens (Bruns & Stieglitz, 2012; Kwak et al., 2010).

Hashtags may go viral on Twitter as more people begin to use them in a short period of time (Bruns & Burgess, 2011), receiving an initial increase of public engagement and attention (Kwak et al., 2010). Trending hashtags may not last long (Asur et al., 2011), and depending on the topic of discussion and how important it is for the public, the focus shifts elsewhere (Lehmann et al., 2012). Trending topics and hashtags represent what issues public attention has shifted towards (Kwak et al., 2010) and represent a community of online users who attend a unique topic or event for a limited period (Lehmann et al., 2012).

The mechanisms by which Twitter identifies the top trending topics and hashtags (Kwak et al., 2010) or what causes some topics to become widely popular are not clear (Asur et al., 2011). Nonetheless, such popularity peaks are of great relevance to identify the issues that are the focal point of the public. As such, trending hashtags are suitable means to be used in the framing analysis of social media data.

Using hashtags facilitates the analysis of public opinion on social media and mitigates the subjectivity issue in data analysis, because they are user-generated metadata that can be used to identify conversations around a certain topic. Hashtags, similar to photographs (Schwalbe & Dougherty, 2015), make it easy for researchers to understand what the tweet is about as they are the commonly accepted public signals for framing and presenting an event or topic among all social media platforms. While framing research on social media has focused mostly on analyzing social media posts, the question of how issues are framed by the public through hashtags has remained relatively underexamined.

Content analysis is a dominant method for analyzing and identifying frames on social media (e.g., Van der Meer & Verhoeven, 2013) and in non-social media contexts (e.g., Semetko & Valkenburg, 2000). Matthes and Kohring (2008) noted that a major issue with identifying frames through content analysis is that it involves researchers' subjective biases in analyzing and coding the text differently. Researchers' subjective biases question the validity and reliability of content analysis and the results (Matthes & Kohring, 2008). Subjectivity is nearly impossible to avoid (Van Gorp, 2010); however using hashtags to identify frames mitigates the subjective role of the researcher in frame analysis because hashtags have a "classificatory function" of indicating what a social media post is about (Zappavigna, 2015). Therefore, hashtags enhance the researcher's capability to describe online information (Trant, 2009) and identify "textual aboutness" (Kehoe & Gee, 2011) of social media posts. In some cases, hashtags may not stand alone in understanding textual aboutness because textual aboutness can be sensitive to context. For instance, a hashtag might reflect 2 different meanings simultaneously (Zappavigna, 2015).

The Effect of Frames on Public Attention on Social Media

There is no standard way for measuring public attention on social media (Silver & Andrey, 2019). However, some previous studies have used the tweet activity, such as the retweet frequency, to measure public attention (Ripberger et al., 2014; Silver & Andrey, 2019). Ripberger et al. (2014) studied public attention by assessing the number of tornado-related tweets posted on Twitter, and assumed that the increase in the number of tornado warnings and number of tornado watches (issued by 2 different institutes) led to an increase in the number of tweets (representing public attention). Chew and Eysenbach (2010) also indicated a coincidence between major H1N1 news and the frequency of H1N1 tweets in April 2009. The presence of a relationship between tweet activity and public attention has been also shown in other studies about swine flu (Szomszor et al., 2010) or influenza (Lampos & Cristianini, 2010).

None of the framing studies on COVID-19 (Benziman, 2020; Ogbodo et al., 2020; Park et al., 2020; Poirier et al., 2020; Wicke & Bolognesi, 2020; Yu et al., 2020) have identified the effect of frames on public attention. This study investigates the effect of COVID-19 frames on Twitter on public attention, by taking a new approach for measuring public attention that is more accurate than the methods used in past studies. It not only measured tweet activity (i.e., number of likes and retweets a frame receives) but also how many unique Twitter users have adopted a frame. In this new approach, public attention was measured by evaluating the score of public engagement with frames and the score of public adoption of frames (see Methods, Measuring Public Attention). In this study, public engagement refers to the number of likes and retweets each frame receives, and public adoption is assessed by the number of unique users in each frame category (DeMasi et al., 2016).

METHODOLOGY

Data Collection

Twitter was the primary source of data collection in this study. The *get_trend* function from the *rtweet* package was used in the R software to collect trending hashtags related to COVID-19 on Twitter in the March of 2020. Additionally, the Trend tab on the Twitter website was observed at least 3 times a day for the entire month of March 2020 to track and record trending hashtags. The trending hashtags identified by the *get_trend* function were exactly similar to those identified by using the Trend feature on Twitter. In March 2020, 22 trending hashtags in the US related to COVID-19 were identified. Additionally, the trending hashtags from each day were searched in the search box of the Twitter website to find other relevant hashtags and achieve a greater degree of reliability in data collection. For instance, by searching #QuarantineLife, a trending hashtag on March 16, 2020, additional hashtags, including #QuarantineDogs and #QuarantineCats, were identified and collected.

This study then collected the tweets that contained at least one of the trending or associated hashtags. The *search_tweets* function from the *rtweet* library was used to collect tweets by the R software and the streaming application programming interface (API). R, Salesforce's Social Studio, and Brandwatch were the tools used to collect tweets. Overall, 694,582 tweets written in English from March 1, 2020, to March 31, 2020.

This study removed the retweets in the dataset to only analyze the initial tweets posted by people on Twitter. The quote tweets (i.e., the retweets with comments), representing the original comments posted by Twitter users, were also collected, and analyzed.

Bot Accounts Removal

Bots are automated accounts that can manipulate and impact public attention on social media (Ferrara, 2020). Ferrara (2020) indicated that bots were active during the COVID-19 pandemic and found that hashtags like #bitcoin, #smartnew, and #grrreatwakening were mostly posted by bot accounts on Twitter (Ferrara, 2020). Thus, 269,854 (269,854/694,582, 38.85%) tweets posted by bot accounts were removed in this study to increase the validity of the results, leaving 424,728 (424,728/694,582, 61.15%) tweets in the dataset.

The default model of the *tweetbotornot* package was used to remove bot accounts (Kearney, 2019). It is 93.53% accurate in classifying bots and 95.32% accurate in classifying nonbots. It uses user-level features (e.g., bio, location, number of followers and friends) and tweet-level features (e.g., number of hashtags, mentions, capital letters) of Twitter accounts to identify bot accounts (Kearney, 2019). Accounts that received a score of at least 50% or a probability of 0.5 were considered bots and removed (Davis et al., 2016).

Thematic Analysis to Identify Frames

Hashtags were the main unit of analysis in this research to identify frames. The frames are primarily informed by the classification of trending hashtags and other collected

hashtags to different categories. Additionally, to identify the frames about COVID-19 in the public opinion on Twitter, thematic analysis was used. Thematic analysis is a method that provides a detailed description of the textual data (Lindekilde, 2014). In this research, public opinion includes all Twitter users such as workers, doctors, officials, journalists, politicians, teachers, and any other group on Twitter.

In thematic analysis, the judgment of the researcher or analyst is adequate for identifying themes (Lindekilde, 2014). The researcher analyzes the text and identifies themes within the “surface meanings of the data” without looking for anything beyond the text (Braun & Clarke, 2006, p. 84).

The thematic analysis helped to provide a more detailed and nuanced description of hashtags and find repeated patterns of meaning (Lindekilde, 2014). The contents of up to 100 randomly selected tweets were checked to ensure an alignment between the hashtags and the contents of tweets. For instance, #WashYourHands, #HandWashing, #SafeHand, #SafeHands, and #HandWashChallenge were classified as one category named “hand hygiene.” Using thematic analysis, this study analyzed the content of the tweets associated with these hashtags to ensure they were related to hand hygiene. The thematic analysis also helped provide a more accurate description of this category. In some cases, the thematic analysis helped to redefine the theme assigned to a set of grouped hashtags.

Five phases were followed to analyze the themes in the tweets (Braun & Clarke, 2006). Figure 1 presents the workflow visualization for the 5 phases of the thematic analysis (Braun & Clarke, 2006). In the first phase, researchers familiarized themselves with the data (Braun & Clarke, 2006) by reading the hashtags and the tweets associated with them several times before coding. It helped researchers obtain some knowledge of the hashtags, related tweets, and the initial list of ideas and themes.

In the second phase, initial codes were generated from trending and associated hashtags (Braun & Clarke, 2006). Hashtags were used to describe what a particular tweet was

about and to create codes. For instance, #ToiletPaperPanic is a hashtag referring to the public panic for the possible shortage of toilet paper during the early days of the pandemic, or #WashYourHands is a hashtag that emphasizes the importance of hand hygiene to prevent contracting the COVID-19 virus.

In the third phase, codes were analyzed and classified into potential themes and sub-themes (Braun & Clarke, 2006). For instance, the following set of hashtags – #SocialDistancing, #SocialDistancing, #KeepYourDistance, #PhysicalDistancing, #SocialDistance, #SocialDistancingNow, #YouAreTooClose, #DontBeASpreader, and #StoptheSpread – and the tweets associated with them helped to identify and propose the “social distancing” theme.

In phase 4, the themes were reviewed and, when necessary, were combined, refined, or separated (Braun & Clarke, 2006) to generate the final themes. In the fifth phase, the themes were clustered into frames. Concise names were assigned to the themes to help readers comprehend the theme’s meaning (Braun & Clarke, 2006).

Measuring Public Attention

To measure public attention to frames on Twitter, this study used the score of public engagement with frames as well as the score of public adoption of frames on Twitter. Following DeMasi et al. (2016), this study defined public engagement as the extent to which users engage with a frame.

Public engagement was measured by the number of times a given frame had received at least one like or retweet divided by the frequency of that frame in the entire dataset. The lowest public engagement score that each frame could receive was 0, with a maximum of 1 (see Table 3). In this study, public adoption refers to how broadly Twitter users adopt a frame. High adoption indicates a diverse community with many unique users who have posted tweets with hashtags in each frame. Low diversity shows a tight community with only a few users posting tweets with the hashtags in a given frame multiple times (DeMasi et al., 2016).

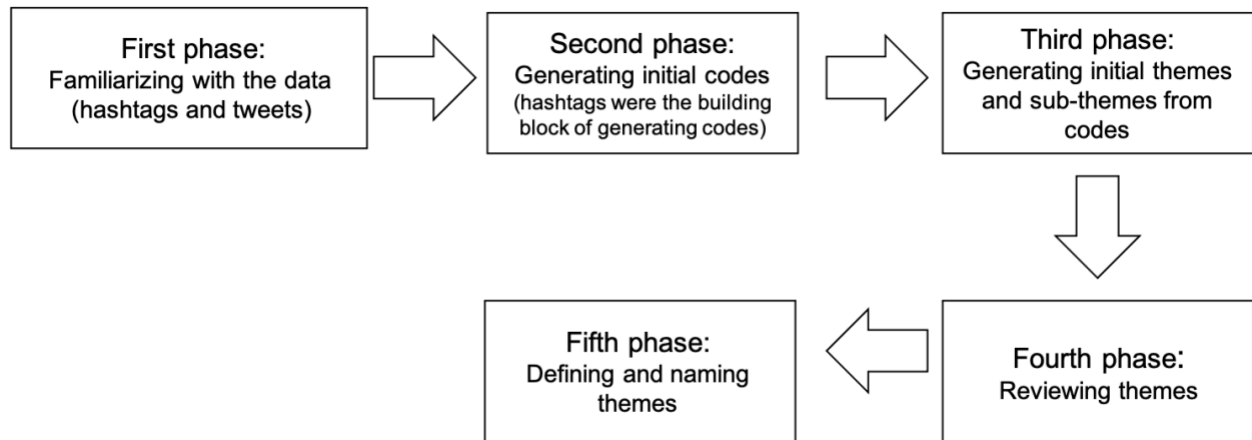


Figure 1. The workflow visualization for the 5 phases of the thematic analysis.

Public adoption was measured by the number of unique Twitter user accounts in a given frame divided by the frequency of the frame (DeMasi et al., 2016). The public adoption score ranges from 0 to 1 as the minimum and maximum scores, respectively (see Table 4).

FINDINGS

Framing of COVID-19 on Twitter

This study indicated 9 categories of frames, along with hashtags that characterized what each frame described, as presented in Table 2. Table 3 shows that “public health guidelines,” was the most frequent frame followed by “quarantine life,” “solidarity,” “evidence and facts,” “call for action,” “politics,” “post-pandemic life,” “shortage panic,” and “conflict.” The results indicated that frames represent a set of consequences of COVID-19.

Public Health Guidelines

Public health guidelines consisted of several main themes, including isolation, social distancing, hand hygiene, face hygiene, preventive tips, and awareness. Isolation included hashtags used to encourage and advise people to isolate themselves from others to prevent the spread of the virus. Some of the hashtags in this category, such as #StayHomeStayHealthy or #StayHomeSaveLives, positively motivate people to self-isolate by staying home. This frame also included the recommendations people made to call others’ attention to the precautionary measures required to reduce the chance of being infected by the virus, such as practicing social distancing or face and hand hygiene, using hashtags such as #SocialDistancing, #WashYourHands, and #WearAMask. Sometimes people utilized hashtags with a sense of humor and positive sentiments, such as #YouAreTooCloseSelf or #HowtoKeepPeopleHome, to frame their perspectives regarding public health guidelines.

Other hashtags in this frame, such as #CoronaVirusTips, were used to provide guidelines and tips about various aspects of the virus, including how to clean smartphones, wash hands, and do contactless delivery of food. Additionally, this frame included tips for preventing potential exposure to the virus. For instance, #CoronaVirusPrevention was used to show how police departments should prevent potential disclosure and provide coronavirus prevention tips for people with disabilities.

Quarantine Life

Quarantine life contained several themes that focused on people's daily lives during the quarantine. People used various hashtags to share stories, pictures, or videos of their home offices, the homeschooling of kids, and their pets. Pet owners used hashtags such as #QuarantineCats or #QuarantineDogs to share humorous content about their living experiences in isolation.

#After3WeeksWithMyFamily and #SideEffectsofQuarantineLife were used to post messages along with photos or videos, often to make fun of the daily experiences of people and actual difficulties they were dealing with during the pandemic. Quarantine life also focused on the impact of the pandemic on how people worked and learned during the quarantine. People posted videos or pictures of themselves using hashtags such as #RemoteLearning, #DistanceLearning, #RemoteWorking, or #OnlineLearning to show they were working or learning from home.

Solidarity

Solidarity focused on inspiring and encouraging messages and giving hope to each other; social support; providing voluntary services to communities; acknowledging health care professionals; and emphasizing unity. People used hashtags such as #StayStrong or #TogetherApart to inspire "staying home together" during the pandemic. #CoronaWarriors, #ClapForCarers, #HealthCareHeroes, and #ClapForOurCarers were used to show appreciation to the frontline workers in fighting the pandemic, namely health care professionals.

Table 2. Framing of the COVID-19 pandemic in public opinion on Twitter.

Hashtags** as the building blocks of frames		Descriptions of tweets containing hashtags	Themes***	Frames
1	#StayHome*, #StayHomeSaveLives*, #StayAtHome*, #StayHomeStaySafe, #StayHomeStayStrong, #StayHomeStayHealthy, #StayInside #SaferAtHome, #SelfQuarantine, #StayHomeStaySafe, #SelfIsolation, #SelfIsolating	Encouraging and advising people to stay home to prevent from spreading of the virus.	Isolation	Public health guidelines

** The hashtags found by searching in the search box of the Twitter website (i.e., hashtags associated with trending hashtags) are labeled by the asterisk sign (*). Although, trending and hashtags associated with them were the main building blocks of identifying frames, other hashtags in the dataset that were relevant to at least one of the frame categories were also added to the Table to enrich the list of hashtags in each category (i.e., the hashtags without the asterisk sign). *** themes represent the consequences of COVID-19.

Table 2 continued.

Hashtags** as the building blocks of frames		Descriptions of tweets containing hashtags	Themes** *	Frames
1	#HowtoKeepPeopleHome*	This hashtag is sometimes used in messages with humorous content to encourage people stay home.	Isolation	Public health guidelines
	#SocialDistancing*, #KeepYourDistance #PhysicalDistancing, #SocialDistance, #SocialDistancingNow, #YouAreTooCloseIf*	These hashtags are used by some people to show how they are practicing social distancing. Some hashtags like #YouAreTooCloseIf are used in tweets with humorous messages about social distancing and its importance.	Social distancing	
	#DontBeASpreader (trending hashtag), #StoptheSpread	Asking people to practice social distancing and other preventative measures to stop the spread of the virus.		

Table 2 continued.

Hashtags** as the building blocks of frames		Descriptions of tweets containing hashtags	Themes***	Frames
1	#WashYourHands*, #HandWashing*, #SafeHand*, #SafeHands*, #HandWashChallenge*	These hashtags are used to show the importance of hand hygiene and encourage people to wash their hands or how to wash hands.	Hand hygiene	Public health guidelines
	#HandSanitizers	It is used to refer to the existence of hand sanitizers in some stores; donation of hand sanitizers; and shortage of them.		
	#FaceMask, #WearAMask, #DontTouchYourFace	Asking people not to touch their faces.	Face hygiene	
	#CoronaTips*, #CoronaVirusTips*, #CoronaVirusPrevention*, #CoronaVirusAwareness*	Providing tips and guidelines, and knowledge about various aspects of the virus.	Preventive tips and awareness	

Table 2 continued.

Hashtags** as the building blocks of frames		Descriptions of tweets containing hashtags	Themes***	Frames
2	#HomeOffice*, #WorkingFromHome #WorkFromHome	These hashtags were used to share pictures or videos of home offices and people working from home.	Home as office	Quarantine life
	#HomeSchooling*, #HomeSchool*	These hashtags were used to share pictures or videos of kids doing their school activities from home.	Home schooling	
	#QuarantineLife (trending hashtag), #Day38OfLockdown, #QuarantineActivities, #QuarantineAndChill	These hashtags were used to show daily life during the quarantine.	Life in quarantine	
	#After3WeeksWithMy Family (trending hashtag), #SideEffectsofQuarantineLife (trending hashtag), #StayHomeChallenge*	Tweets with a sense of humor displaying what people do and how they feel during the quarantine.		

	#QuarantineCats*, #QuarantineDogs*	People used these hashtags to share tweets, often with humorous content, about their pets during quarantine.	Pets and quarantine	
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Table 2 continued.

Hashtags** as the building blocks of frames		Descriptions of tweets containing hashtags	Themes***	Frames
2	#LockDown, #CoronaLockDown, #CoronaVirusLockDown, #ThelockDown	These hashtags represent various aspects of daily life during the lockdown.	Lockdown	Quarantine life
	#OnlineLearning, #RemoteLearning, #DistanceLearning, #RemoteWorking	Impact of the pandemic on how people study, learn, and work during the quarantine.	Remote Working/Learning	
3	#StayStrong*, #StayPositive*, #WeAreInThisTogether, #StayHealthy, #StrongerTogether, #TogetherWeCan, #StayConnected	Inspiring, encouraging, giving hope, and supporting each other as part of a solution to the pandemic.	Social support	Solidarity
	#WeServeAndProtect	It was used to show voluntary services, such as disinfecting facilities, during the pandemic.	Voluntary service to communities	

Table 2 continued.

Hashtags** as the building blocks of frames		Descriptions of tweets containing hashtags	Themes***	Frames
3	#CoronaWarriors, #ClapForCarers #HealthCareHeroes, #ClapForOurCarers	Showing appreciation for frontline workers in fighting the pandemic, specifically health care professionals.	Acknowledging health care professionals	Solidarity
	#TogetherApart (trending hashtag), #AloneTogether, #PlayApartTogether	Emphasizing that the best way to be together is to stay apart until the pandemic is over.	Showing unity	
	#ArmyMissesBTS*	Solidarity for canceled concert of the a South Korean band because of the pandemic.	Solidarity with canceled events	
	#OpenforTakeout*, #OpenForDelivery (trending hashtag), #SupportSmallBusiness #SmallBusiness, #SupportLocal	Supporting small and local businesses and local restaurants that are open for takeout or delivery.	Supporting local and small business	

Table 2 continued.

Hashtags** as the building blocks of frames		Descriptions of tweets containing hashtags	Themes***	Frames
3	#ProtectOurSeniors*, #ProtectSeniors*, #ProtectTheSeniors*, #ProtectTheVulnerable, #ProtectHealthCareWorkers, #ProtectTheAllCareWorkers	Supporting vulnerable groups, such as seniors, and those who are in the frontline of fighting the pandemic, such as healthcare workers.	Supporting vulnerable groups	Solidarity
	#AmazonStrike (trending hashtag), #InstaCartStrike*, #ProtectAmazonWorkers, #EssentialWorkers	Supporting workers and the unsafe working environments during the pandemic.	Supporting workers	

Table 2 continued.

Hashtags** as the building blocks of frames		Descriptions of tweets containing hashtags	Themes***	Frames
4	#CloseTheSchools (trending hashtag), #CloseTheSchoolsNow*, #SchoolClosure*, #CloseTheLibraries*, #CloseTheLibrary*, #CloseTheColleges*, #CloseTheUniversities*, #CloseTheCamps*, #CloseTheDayCare*, #Covid19Walkout, #CloseTheBeaches (trending hashtag), #CloseThe*, #CloseThePubs*, #CloseTheBars*, #ShutItDown	These hashtags are used to ask federal and local governments to shut down public places, like beaches and schools.	Appealing to the authorities to close public places	Call for action
	#FlattenTheCurve	Encouraging people to play their own part in flattening the curve.	Collective responsibility and action	

Table 2 continued.

Hashtags** as the building blocks of frames		Descriptions of tweets containing hashtags	Themes***	Frames
5	#CoronaVirusUpdates (trending hashtag), #CoronaUpdate*	Updates about various aspects of the virus like the total number of deaths, new cases, or new evidence.	Updates on the pandemic	Evidence and facts
	#CoronaVirusTruth	Bringing public attention to the facts about the virus, such as the increasing number of deaths in the USA.	Facts about the virus	
6	#TrumpLiedPeopleDied (trending hashtag), #ChinaLiedPeopleDied (trending hashtag), #FoxNewsLiedAsPeopleDied*, #TrumpPandemic*, #TrumpLiesPeopleDie, #TrumpVirus	Making political officials responsible for their actions, decisions, and policies.	Accountability of political figures	Politics

Table 2 continued.

Hashtags** as the building blocks of frames		Descriptions of tweets containing hashtags	Themes***	Frames
7	#WhenCoronaVirusIs Over (trending hashtag), #WhenILeaveMyHouseAgain (trending hashtag)	Future life and plans once the pandemic is over. Referring to how the world will change or how people will feel after the pandemic. These hashtags sometimes are used in tweets with humorous contents.	Life, feelings, and plans after the pandemic.	Post-pandemic life
8	#Panicbuying (trending hashtag), #ToiletPaper*, #ToiletPaperPanic (trending hashtag), #ToiletPaperCrisis*, #ToiletPaper*, #PanicShopping*, #CoronaPanic*, #ToiletPaperShortage*, , #ToiletPaperEmergency*,	People's reactions in the preliminary phase of the pandemic, such as panic and anxiety to shortage of products, such as toilet paper or bottled water.	Toilet paper panic	Shortage panic

	#ToiletPaperApocalypse*, #ToiletPaperWars			
9	#FilmYourHospital (trending hashtag), #EmptyHospitals*, #FakeNews	Arguments about and disagreements with information, news, and facts related to COVID-19.	Challenging the facts	Conflict

A major theme in solidarity was social support, which consisted of hashtags used to assist various vulnerable populations or services. For instance, #ProtectOurSeniors was used to emphasize the importance of supporting seniors medically, financially, and emotionally. Other hashtags such as #OpenForTakeout, #OpenForDelivery, #SupportSmallBusiness, and #SupportLocal were used to support businesses and acknowledge the (local) stores that were open for takeout or delivery during the pandemic.

Call for Action

This frame refers to a lack of accountability and responsibility in governments for not taking necessary actions to close public places. Hashtags such as #CloseTheSchoolsNow and #CloseThePubs were used by people to ask federal and local governments to take prompt action to shut down public places, like beaches and schools. This frame also consisted of hashtags that were used to argue and complain about people's lack of compliance with public health guidelines. For instance, #CloseTheBeaches was used in tweets to emphasize that a public space like beaches should be closed to prevent people from going to the Florida's beaches during the pandemic.

Evidence and Facts

This frame reflected people's perspectives about the updates, realities, and truths related to various aspects of the pandemic, such as the total number of deaths, new cases, discharged patients, and further evidence about how the virus spreads. For instance, #CoronaVirusUpsdates was used on March 29, 2020, to refer to the emerging hotspots of coronavirus and bring to public attention that New York remained the worst-hit US state. Another hashtag in this category was #CoronaVirusTruth, used by people to share information about what they thought were the true facts about the pandemic, such as the increasing number of deaths in the US and across the globe.

Politics

This frame reflects the accountability of politicians for their policies and actions during the pandemic. Hashtags such as #TrumpLiesAboutCoronavirus, and #TrumpVirusCoverUp were used to hold political officials accountable for their bad policies, decisions, and actions regarding the COVID-19 pandemic. The tweets in this category often had a negative sentiment. For instance, #TrumpLiedPeopleDied was used to show a lack of transparency and lack of timely action to control the virus, not taking the pandemic seriously, and not following public health guidelines and policies. #ChinaLiedPeopleDied was, on the other hand, used to make China responsible for the transmission of the COVID-19 virus to other countries.

Post-Pandemic Life

This frame focused on the positive sentiments surrounding people's plans, feelings, and life after the pandemic. The main hashtags in this category were #WhenCoronaVirusIsOver and #WhenILeaveMyHouseAgain that were posted with tweets with a sense of humor to discuss what the future may look like when the pandemic is over. For instance, people framed their opinion about the future, using hashtags in this category, to refer to the food they like to eat; to describe the places or people they enjoy visiting; to recommend things people should avoid doing, like eating animals; to emphasize that the world would be a cleaner place; and suggest that people would love and respect nature more than before, after the pandemic.

Shortage Panic

This frame showed the panic about the shortage of products when the pandemic had just started in March 2020. Shortage panic refers to public reaction to and anxiety about the shortage of resources, including bottled water, toilet paper, hand sanitizer, and food. Most tweets in this category contained an image or video showing empty shelves in stores or people lined up trying to purchase products such as toilet papers.

This frame demonstrated uncertainty in the public about how much supplies were needed because the future was unpredictable (Kirby, 2020). The uncertainty about the pandemic led to an “exaggerated sense of urgency and a fear of scarcity,” which resulted in actual scarcity (Kirby, 2020).

Conflict

Conflict refers to arguments and disagreements among people. Hashtags such as #FilmYourHospital or #EmptyHospitals were used to imply that COVID-19 was not as severe as stated by the media, governments, or health officials. Some people used these hashtags to frame their disapproval of the lockdown or social distancing or to suggest that COVID-19 is not real. Another hashtag in this category was #FakeNews, which was used to share opposing views about various aspects of the pandemic. It was also used to show disapproval with the information and news spread about the virus, mostly by the news media or politicians from both the Democratic and Republican parties. #FakeNews was sometimes used by a group to argue in favor of issues related to COVID-19, and other times, by another group to argue against those issues (see Van Gorp, 2010).

Public Attention to Frames

Public attention to frames was assessed using the 2 measures of “public engagement” and “public adoption.” Public engagement shows how engaging a frame has been on Twitter, counted by the number of retweets and likes a frame had received. Public adoption refers to the number of unique Twitter user accounts in a given frame category, divided by the frequency of frames in that category (Stephenson, 2018).

Table 3 shows public engagement with each frame. “Call for action” had the highest engagement (0.68), followed by “conflict” (0.67) and “evidence and facts” (0.59). Table 4 shows the public adoption score for each frame. “Post-pandemic life” (0.99) had the highest adoption score, followed by “call for action” (0.92) and “shortage panic” (0.91).

Table 3. Public engagement with frames.

	Frame	Frequency of frame	Yes*	No	Public engagement score (Yes/Yes+No)
1	Public health guidelines	171,009	94,545	76,464	0.55
2	Quarantine life	86,983	48,701	38,282	0.56
3	Solidarity	46,164	25,253	20,911	0.54
4	Evidence and facts	31,819	18,874	12,945	0.59
5	Call for action	31,809	21,881	9,928	0.68
6	Politics	24,346	11,903	12,443	0.49
7	Post-pandemic life	20,442	11,439	9,003	0.56
8	Shortage panic	16,815	9,321	7,494	0.55
9	Conflict	3,550	2,384	1,166	0.67

* Each frame receiving at least a retweet or like was labeled as “Yes,” otherwise they were labeled as “No.”

Table 4. Public adoption of frames

	Frame	Frequency of unique users (U)	Frequency of frame (F)	Public adoption score (U/F)
1	Public health guidelines	142,105	171,009	0.83
2	Quarantine life	75,439	86,983	0.87
3	Solidarity	37,424	46,164	0.80
4	Call for action	29,134	31,809	0.92
5	Evidence and facts	27,957	31,819	0.88
6	Politics	21,724	24,346	0.89
7	Post-pandemic life	20,149	20,442	0.99
8	Shortage panic	15,255	16,815	0.91
9	Conflict	2,095	3,550	0.60

The distribution of public engagement and public adoption is illustrated in Figure 2. According to this Figure, although conflict had the lowest frequency ($n=3550$), it received the second-highest engagement score (0.67). Public health guidelines had the highest frequency (171,009), followed by quarantine life ($n=86,983$); however, their public adoption and engagement scores were not high. Pearson correlation did not show any correlation between public adoption and public engagement: $r_s = -0.46$, $P = .18$.

Figure 3 presents the distribution of public engagement with and public adoption of frames in terms of frame frequency. No meaningful pattern was observed in frame engagement and adoption based on frequency. Pearson correlation showed no correlation between engagement and frequency, ($r_s = -0.26$, $P = .46$) nor between adoption and frequency ($r_s = 0.13$, $P = .70$). The insignificant results indicates that a frame receiving high adoption by the people may not necessarily achieve a high engagement (or vice versa).

DISCUSSION

This study analyzed the trending hashtags and hashtags associated with them in the US in March 2020, during the initial weeks of the COVID-19 pandemic. The results indicated 9 frames in public opinion about the COVID1-9 pandemic on Twitter: “public health guidelines,” was the most frequent frame followed by “quarantine life,” “solidarity,” “evidence and facts,” “call for action,” “politics,” “post-pandemic life,” “shortage panic,” and “conflict.” These frames and the hashtags within them such as #SupportSmallBusinesses or #StayPositive can be used to identify the types of information that should be delivered during any public health crisis, specifically the initial phase of a crisis. Furthermore, some of the frames such as solidarity, evidence and facts, call for action, politics, shortage panic, and conflict might be present in any local or global crisis such as social movements, earthquakes, tornadoes, hurricanes, and floods. For instance, the solidarity frame can be used to design messages to encourage people to show solidarity to those impacted by a crisis.

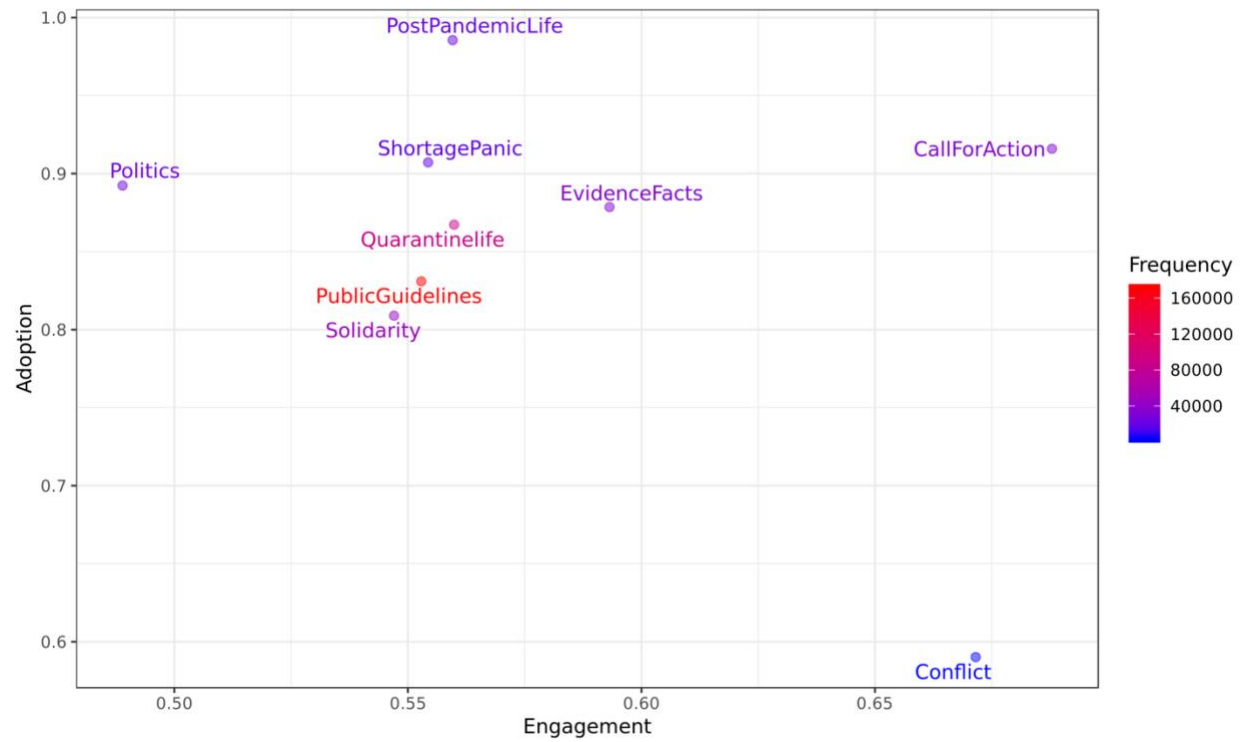


Figure 2. The distribution of public engagement with frames and public adoption of frames.

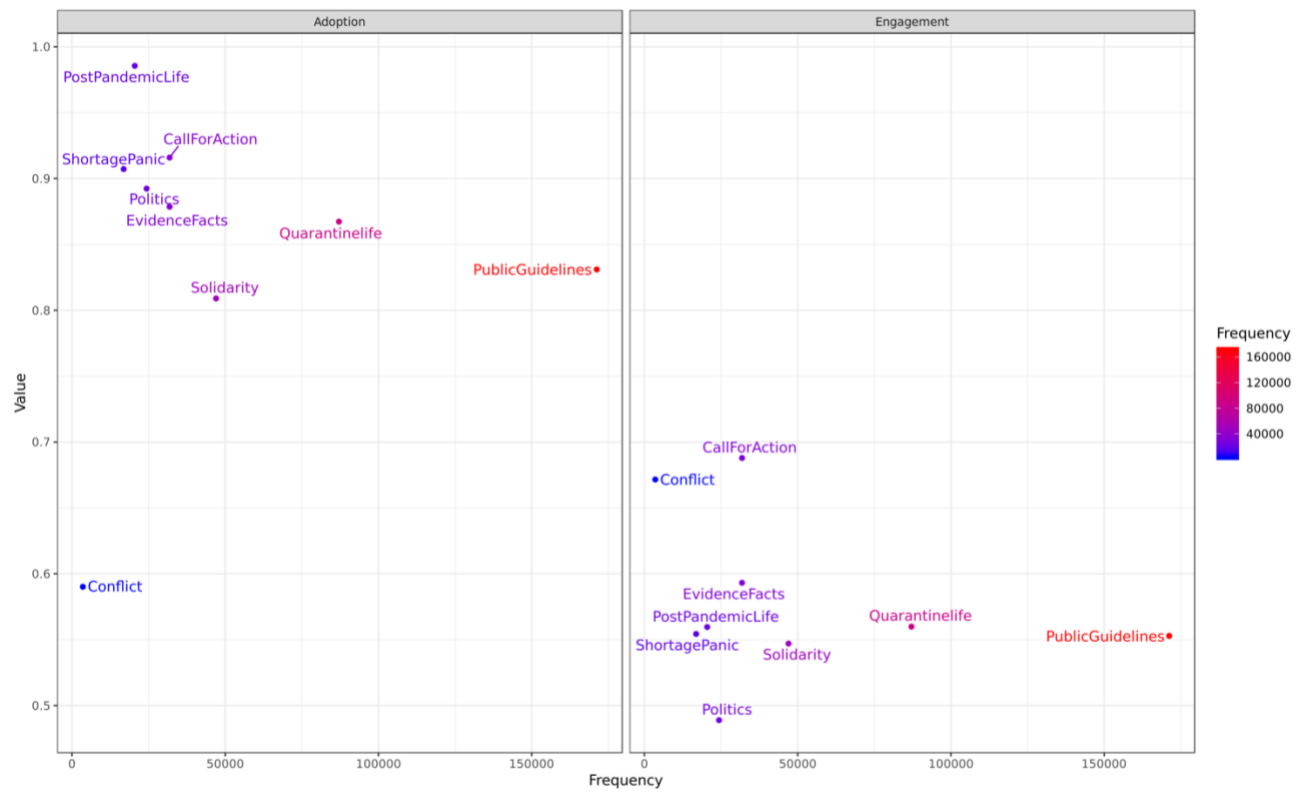


Figure 3. The distribution of public engagement with frames and public adoption of frames, based on frame frequency.

This study also measured public attention to frames by assessing the amount of public engagement with frames and public adoption of them. Among all frames, “call for action” had the highest engagement score, followed by “conflict” and “evidence and facts.” Additionally, “post-pandemic life” had the highest adoption score, followed by “call for action” and “shortage panic.”

According to Price and Tewksbury (1997), framing is more effective when it is relevant to people, such as when the frames resonate with the audience’s beliefs or ideology (Nisbet, 2010). The effects of frames on public opinion could be more substantial when the quality or logic of the argument and source credibility are more reliable (Chong & Druckman, 2007a).

The frames with greater public attention could be used strategically to design messages that affect public opinion more efficiently during public health emergencies. These frames could also be used to increase the performance of social media posts and encourage public compliance with health messages.

Theoretical Contributions and Implications

This study informs framing theory and research in several ways, mentioned in the following sections.

Frames as the Manifestation of COVID-19 Consequences

This research informs the framing theory by indicating that framing analysis of public opinion on social media via hashtags is valuable not only in understanding public opinion about various aspects of the pandemic but also in recognizing the consequences of the pandemic on people’s lives, such as panic over the shortage of products.

The findings indicated that frames are the manifestation of COVID-19 consequences. The consequences discussed by people on Twitter about COVID-19 could be classified and analyzed based on whether (1) they were exclusively related to COVID-19, such as hand hygiene or isolation (i.e., people are isolated, or people wash their hands because of

COVID-19); (2) consequences could be related to any health crisis such as social support of vulnerable groups (i.e., vulnerable groups require social support in any pandemic); and (3) consequences were generic, irrespective of COVID-19, such as homeschooling or remote working (i.e., some people homeschooled or worked remotely even before the pandemic).

Frames Promote Collective Interest

This study also informs the framing research by showing that hashtags can be used to frame messages in a way to promote collective interest by motivating social media users to adopt good behaviors. Some of the hashtags identified in this study, such as #StayHomeStayHealthy, would motivate people to stay home which may consequently promote collective interest among people. Another hashtag was #SocialDistancingNow used to motivate Twitter users to prevent the potential transmission of COVID-19 for the public good. #WearAMask is another hashtag used to promote a collective interest in public to prevent the spread of the virus rather than merely preventing oneself from contracting it (Van Der Linden & Savoie, 2020).

Conflict and Disagreement with Evidence and Facts

People used the “conflict” frame to discredit the evidence, facts, and updates about the COVID-19 virus, such as its fatality rates. Previous studies indicate that the news media sometimes use the “conflict” frame to report disagreements and arguments among people or groups to capture more audiences (Semetko & Valkenburg, 2000). Using the conflict frame in social media posts can “increase the perceived seriousness and news value of an event” (Valenzuela et al., 2017, p. 806).

The conflict frame seems to be important in both the news media and public discourse during public health emergencies. Shih et al. (2008) stated that the conflict frame (defined as the arguments and disagreements among news sources) is the mainframe in the media coverage of public health pandemics. Park et al. (2020) also found that conflict was a main frame in the Korean news media tweets about COVID-19. The popularity of

the conflict frame demonstrates there are always groups of people with disagreements about facts and evidence during public health emergencies.

This frame had the lowest frequency and lowest public adoption score among all frames identified in this study. A few previous studies have also indicated that news with conflict frames has been shared less on social media than the frames without conflict frames (Valenzuela et al., 2017). However, in this study, the conflict frame received the second-highest score for public engagement, indicating that hashtags with conflicting information, such as #FilmYourHospital, are highly engaging on social media, despite their low frequency. A low adoption score with a high engagement score could indicate a focused community structure (DeMasi et al., 2016).

The “conflict” and “evidence and facts” frames indicated the presence of a chain of reactions, in that in response to the people who posted information about facts and updates related to COVID-19 (i.e., the evidence and facts frame), another group of people used the conflict frame to challenge those facts and updates (i.e., the conflict frame). Some people would then, in turn, react to the conflict frame by sharing evidence and facts about the virus.

Vulnerable Groups

Our results indicated that framing analysis of public opinion on social media could be used to identify groups of vulnerable populations (e.g., including seniors, workers, and local and small businesses) and how the people frame their concerns and opinion about the needs of such populations on Twitter. It was found that vulnerable populations needed prompt attention and support during the pandemic. For instance, seniors would require social support, workers need safe workplaces, and local and small businesses need financial support. The findings did not show any hashtag referring to race or ethnic minority groups or health disparity populations, such as refugees, immigrants, homeless individuals, countries with fewer resources, or other marginalized communities. This could be possibly due to the focus of this study on trending hashtags in the US. Overall, framing

analysis through hashtags can be used to identify the populations that need more attention and support during global crises.

Accountability of Gatekeepers

This study identified who, or which groups were responsible for managing the COVID-19 crisis in the public view. The “call to action” frame indicated that Twitter users held federal and local governments accountable for their lack of actions regarding the closure of public places like beaches or restaurants. The “politics” frame also demonstrated people’s reaction to politicians’ decisions, policies, and insufficient actions during the pandemic. The politics frame included hashtags that showed who were responsible for this crisis in the public view. For instance, many hashtags in this category were used to make the US President accountable for the increasing number of COVID-19 cases and deaths. This frame could also show a lack of trust between politicians and the public, which often occurs during the initial phases of a pandemic (Cairney & Wellstead, 2020).

The Use of Humor in Public Health Messages

The results in this study inform the framing research by showing that hashtags, such as #QuarantineCat or #HowToKeepPeopleHome, can be used to frame and share messages with humorous content. These hashtags were not directly related to COVID-19, but were generated and used by Twitter users during the pandemic. Additionally, people used such hashtags to share their experiences of living in isolation. Some tweets with these hashtags were used to make fun out of the lived experience and actual difficulties people were dealing with during the pandemic. The use of humor in tweets has been previously reported in past studies (Jaiswal et al., 2019; Kopper, 2020). For instance, Kopper (2020) noted that the use of humor in diplomatic tweets has a conflict-mediating role. In this study, the use of humor in public health tweets had a role in mitigating the public anxiety or fear as the consequences of the pandemic. Perhaps people used humor in tweets to convey complex public health messages that are more attractive to audiences.

Although humorous hashtags may simply not seem appropriate for use in public health communication, they can make up part of a broader information-sharing strategy. For example, to communicate safety guidelines, social media posts could be labeled with humorous hashtags that are appealing. The safety-related messages may then be transferred to and adopted by the public through such hashtags. Additionally, practitioners, activists, organizations, and authorities can actively embed relevant and meaningful hashtags into their posts that are framed more generally within appealing concepts.

Practical Implications

Designing Health Messages

The frames found in this study can also facilitate the communication of various aspects of COVID-19 or any future health crisis on social media. They can be used to serve as a starting point for designing effective messages to address people's needs and concerns during future public health crises (Park et al., 2020). For instance, based on the current research, it can be suggested that health messages should be communicated with empathy, as also proposed in the study by Hyland-Wood et al. (2021). These frames can support the public in the expression of their feelings and opinions during global crises (Wicke & Bolognesi, 2020). The frames can also be used to influence public opinion, behavior and actions about critical and complex issues related to COVID-19 (see Hemphill et al., 2013).

Governments, practitioners, organizations, activists, and authorities can take advantage of hashtags to frame their messages to inform the public about the consequences of lack of adherence to public health guidelines. For instance, governments and public health officials need to share actionable guidelines with citizens during public crises and inform them about what is happening. These activities require understanding of how messages should be framed and presented so that risk communications are accepted and adopted by the public (Oppenheim et al., 2019). If health communication officers, political officials,

and other authorities wish to encourage citizens to follow public health guidelines, stay optimistic and be supportive during a health crisis, they can frame their messages using the hashtags identified in this research. For instance, a message by WHO could be framed as follows: “#WeAreInThisTogether: #StayStrong at home and post a video or picture of your dogs or cats in #Quarantine. Use #QuarantineCats or #QuarantineDogs to help others see your posts.”

Issues and their Roots

The results indicated that framing can also be used to identify the roots of the issues discussed by people on social media during public health crises. For instance, framing could be used to understand when, how, and about what topics false information is being distributed. The results indicated that #FilmYourHospital was a hashtag used by people to frame disagreements against evidence and facts related to the pandemic. Once such problems and their roots are discovered, officials can find solutions, which, in this case, would be to neutralize and thwart false information dissemination.

Analyzing public opinion on social media can be used to identify what people panic about during a public health crisis. Another issue discussed by people was the “shortage panic,” referring to people’s reactions to the shortage and unavailability of products during the early days of the pandemic in March 2020. This panic could possibly be due to uncertainty in the public about what will happen in the future, lack of real-time communication with the public, or lack of trust between people and government officials. The study by Naeem (2021) also indicated that uncertainty about COVID-19 triggered people to buy extra necessary food items, which resulted in the buying panic during the COVID-19 pandemic.

Methodological Contributions

This research contributes to the methodology of framing research on social media in several ways, as explained in the following sections.

Accuracy in Data Collection

Many previous studies have used hashtags or even keywords to collect tweets, while in this study we utilized trending hashtags related to COVID-19 as the main source of data collection, which allowed us to collect tweets relevant to the topics that were the focal point of the public in March 2020, when the pandemic had just started globally. Using trending hashtags and the hashtags associated with them allowed us to increase the accuracy of collecting relevant data.

Furthermore, the hashtag search approach is more accurate in identifying relevant tweets than the keyword-based search approach used in some past studies, mainly because hashtags are user-generated metadata assigned to tweets to describe what the tweets are about (Potnis & Tahamtan, 2021). A major issue with the keyword-based search and analysis is that it may result in retrieving extraneous tweets or excluding relevant ones, as stated by Jang and Hart (2015).

Using Trending Hashtags to Identify Frames

Unlike most previous framing studies on Twitter that have solely analyzed tweets to identify frames, this study analyzed hashtags along with the tweets containing them to identify how people framed their opinion about the COVID-19 pandemic. Jang and Hart (2015, p. 13) stated that an effective approach for analyzing frames is “to identify unique components of public rhetoric that clearly represent single frames of a more complex issue.” Hashtags are unique components, generated by users, that represent frames of complex issues on social media. Moy and Bosch (2013, p. 239) noted that frames provide “meaning about social phenomena through the highlighting and packaging of information.” Hashtags can also be used to give meaning to and highlight social phenomena. In the Literature Review section, the rationale for using (trending) hashtags for identifying frames is discussed.

Measuring Public Attention on Twitter

There is no standard way to measure public attention on Twitter. This study contributes to the methodology of framing research by measuring the score of public attention to frames through the use of 2 metrics: public engagement with frames and public adoption of them (DeMasi et al., 2016). Rarely any previous framing research has used this approach to measure the effect of frames on public attention on social media. This approach can also be used to identify the framing effect of the news media on public attention on social media in future studies.

Study Limitations

The study limitations were mostly related to data collection, some of which were beyond our control. For instance, due to the Twitter API restrictions in collecting historical data, all tweets associated with the hashtags could not be collected. It was tried to mitigate this limitation by using 3 software for collecting historical data, as explained in the data collection section.

Another limitation of the study was that sampling tweets based on hashtags may not represent all communications occurred on Twitter. Hashtags may only represent a specific subset of Twitter communications, because not all Twitter users use hashtags in their online communications on social media (Bruns & Moe, 2014; Siapera et al., 2018).

Additionally, this study only collected hashtags and tweets for the month of March in 2020, while collecting data in other months can lead to different results. This research may have missed collecting all trending hashtags about COVID-19 for several reasons. First, Twitter determines emerging and trending topics (topics that are popular at a certain time) based on who the users (researchers who collect the data) follow, their interests, their locations, and other criteria (see Twitter trends FAQs). Second, a hashtag may be trending for a couple of hours, a day, or in rare cases, more than a day. A hashtag that is trending today may not be trending tomorrow, but people may still use the hashtag for a short or long

period of time. The hashtag may disappear temporarily after a few days, may gain attention again in the future, or may disappear permanently (Kwak et al., 2010).

Conclusion

This is one of the first studies that uses trending hashtags in framing analysis of social media data. This study contributes to the framing theory by showing that frames can represent the consequences of a public health emergency, such as the COVID-19 pandemic. The consequences could be (a) exclusively related to COVID-19, such as hand hygiene or isolation, (b) related to any health crisis, such as social support of vulnerable groups, or (c) generic, that are irrespective of COVID-19, such as homeschooling or remote working. Additionally, the findings inform framing theory and research by showing that the methodological advantages of using (trending) hashtags lie not only in their ability to understanding the frames that are the focal point of the public, but also in their potential to allow researchers to measure public attention to those frames. The results indicated that some frames were more appealing than others during a global pandemic, such as “call for action,” therefore receiving greater public adoption and engagement. It was found that the frequency of a frame on social media may not necessarily mean greater public engagement with the frame or public adoption of the frame.

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CHAPTER 3: THE NETWORK AGENDA-SETTING EFFECT OF WHO ON ITS FOLLOWERS ON TWITTER ABOUT THE COVID-19 PANDEMIC

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Tahamtan, I., Potnis, D., Mohammadi, E., Singh, V., & Miller, L. E. (2022). The mutual influence of the World Health Organization (WHO) and twitter users during COVID-19: network agenda-setting analysis. *Journal of Medical Internet Research*, 24(4), e34321, [0.2196/34321](https://doi.org/10.2196/34321).

ABSTRACT

Little is known about the role of the World Health Organization (WHO) in communicating with the public on social media during a public health emergency. More specifically, there is no study about the relationship between the agenda network of WHO's official Twitter account and the agenda network of 7.5 million of its followers on Twitter regarding COVID-19. This study fills in the gap by (a) applying content analysis to 7,090 tweets posted by WHO from January 1 to July 31, 2020, to determine the WHO agenda, and (b) utilizes the quadratic assignment procedure (QAP) to examine the relationship between the WHO agenda network and the agenda network of 6 Twitter user categories, namely "health care professionals," "academics," "politicians," "print and electronic media," "legal professionals," and the "private sector." Additionally, this study performed 98 Granger causality tests to determine what issue in the WHO agenda influenced the corresponding issue in Twitter user categories and vice versa. Content analysis revealed 7 issues in WHO tweets, reflecting its agenda about the COVID-19 pandemic, including "prevention," "solidarity," "charity," "teamwork," "ill-effect," "surveillance," and "credibility." The results of the QAP showed significant and strong correlations between the WHO agenda network and the agenda network of each Twitter user category. These results provide evidence that WHO had an overall effect on different types of Twitter users on the identified issues. For instance, the Granger causality tests indicated that WHO tweets influenced on politicians and print and electronic media about "surveillance". WHO tweets also influenced "credibility" in academics and private sector organizations, and "ill-

effect” in print and electronic media. It was also found that Twitter user categories influenced the WHO agenda on some topics such as “charity,” “prevention,” “surveillance,” and “ill-effect”. This study contributes to the agenda-setting theory by providing evidence that agenda–setting effects vary by Twitter user category and issue type, and that there can be “two-way” or “multiway” agenda-setting effects on social media, where WHO and various categories of social media users influence each other’s agenda.

INTRODUCTION

COVID-19 on Social Media

Social media has changed how online users share and receive news and information on various public health emergencies. A contagious and fatal public health emergency is the COVID-19 virus, declared by WHO as a pandemic on March 11, 2020 (World Health Organization, 2020b). As of July 16, 2021, the virus had affected 188,655,968 people, including 4,067,517 deaths worldwide (WHO, 2021). Right after the outbreak of the virus in China and many other countries, social media became the main technology via which millions of people began sharing and receiving information worldwide about different aspects of the virus.

Organizations such as WHO, CDC, governments, scientists, health care professionals, and news agencies used social media to share updates, guidance, expert knowledge, research and development initiatives, and preventive measures with the public.

The shared information on social media can bring public attention to issues that are of serious concern, consequently affecting public opinion (Rodriguez & Dimitrova, 2011). For instance, health information communicated through social media, labeled with meaningful and relevant hashtags, would help people

understand prevention, treatment, and recovery approaches for mitigating the consequences of public health crises (Nasrallah et al., 2019).

The COVID-19 Infodemic

Besides its many benefits, the spread of information on social media led to the flooding of low quality and unverified information about COVID-19 (Brennen et al., 2020; Broniatowski et al., 2021; Cinelli et al., 2020), making the pandemic an “infodemic” of misinformation as declared by WHO on September 23, 2020 (World Health Organization, 2020a). Infodemic refers to the overabundance of information that includes disseminating wrong information, which can undermine the public response to health guidelines (World Health Organization, 2020a). The overabundance of false information during pandemics can increase the public’s uncertainty about the situation and what will happen next (Park et al., 2020).

Keeping the public informed by providing correct information is critical during infodemics (Hua & Shaw, 2020). People receive information from various sources, mainly the news media, which can disseminate biased information due to their politically biased and partisan stance on health information, consequently impacting public opinion and behavior (Van Scoy et al., 2021). For instance, Van Scoy et al. (2021) showed that the people trusting and receiving information from *Fox News* took fewer preventive behaviors and showed more risky behaviors related to COVID-19 than those who received information from *CNN*. Thus, even trusted sources of information are likely to produce biased and irrelevant information (Brennen et al., 2020). Brennen et al. (2020) found that approximately 20% of misinformation about COVID-19 on social media with about 70 social media engagements were posted by gatekeepers, such as politicians, celebrities, and other influential public figures. Relying on these gatekeepers as sources of information related to COVID-19 can sometimes develop biased opinions or a false reality about COVID-19.

Potential Solution

During an infodemic of misinformation on social media, governments and health authorities should take quick action to make the public aware of the existing challenges and mitigate corresponding consequences (Hua & Shaw, 2020). It is essential that the sources of health information that are trusted by the public, such as WHO (Van Scoy et al., 2021), make it part of their agenda to regularly communicate various aspects of the pandemic to the public to manage the infodemic and decrease uncertainty in society. An agenda can be defined as the issues, topics, or events present in the public or media or any other medium at a given time (Christie, 2006). According to WHO, health communication should be used effectively in every aspect of public health issues, such as disease prevention and health promotion (Van Bavel et al., 2020).

WHO should then (and can) use social media to share reliable information and guidance with the public and fight against the spread of rumors and misinformation related to the pandemic (Merchant & Lurie, 2020). WHO used social media from the beginning to communicate timely and reliable health information to create public awareness of salient issues and combat misinformation about the COVID-19 pandemic (Zarocostas, 2020).

Research Questions

Several studies report the increasing reliance of people on WHO to obtain reliable information related to COVID-19 (Van Scoy et al., 2021). To understand and explore the role of WHO in setting a public health agenda for different types of social media categories, an understudied area of research in health communication and information science, this study investigates the following research questions:

RQ1. What is the WHO agenda about the COVID-19 pandemic on Twitter?

RQ2. How do WHO and different categories of WHO followers on Twitter affect each other's agenda regarding COVID-19?

These research questions help us (a) understand the extent to which WHO has been successful in setting its agenda about COVID-19 on Twitter and (b) propose how WHO can more effectively create information-related benefits for different categories of users on Twitter during public health emergencies.

This study adopted the agenda-setting theory (McCombs & Shaw, 1972) as a lens to address the research questions, because it can be used to understand and explain the impact of gatekeepers in shaping public agenda on issues such as political debates, social movements, and health crises. The importance of agenda-setting is that it can be used by gatekeepers such as the news media to tell the public what critical issues a country is facing (Guo & Vu, 2018) and to impact public opinion about those issues (McCombs & Valenzuela, 2007). This study is specifically focused on network agenda-setting model (Guo & McCombs, 2011) which states that the salience of interrelationships among attributes (e.g., social distancing, handwashing, face covering) of an issue (e.g., COVID-19) emphasized by gatekeepers can be transferred to (affect) the public agenda (Guo & McCombs, 2011).

LITERATURE REVIEW

Agenda-Setting

Gatekeepers such as the news media determine which issues are important in society and consequently set the public agenda around those issues (McCombs & Shaw, 1972). When an issue is being shared frequently and prominently, the public may also come to perceive them as important (Coleman et al., 2009). For instance, the presentation and repetition of “social distancing” by WHO on social media can

make the public perceive it as an important attribute of COVID-19 that should be given considerable attention.

The agenda-setting theory (McCombs & Shaw, 1972) is about transferring the salience of issues (e.g., COVID-19) from gatekeepers, namely the news media, to the public, suggesting that gatekeepers can tell people which *issues to think about*. Agenda-setting is also about transferring the salience of the issue attributes (e.g., social distancing, hand hygiene, face covering) to the public, suggesting that gatekeepers can tell people *how to think about* those issues (McCombs & Valenzuela, 2007). For example, COVID-19 is a public health issue that has a variety of attributes. Gatekeepers such as journalists and politicians can set an agenda with a focus on COVID-19 to tell the public to also think about this issue and, among its various attributes, think about, for instance, social distancing, hand hygiene, and face covering.

Agenda-Setting Effect

Agenda-setting research also investigates the effect of the issues promoted by gatekeepers on public opinion (Reese et al., 2001). Agenda-setting proposes that the repetition of messages about public issues or anything that is the focus of attention by the news media can influence people's minds (Coleman et al., 2009). As a result of the repetition of issues, people mentally connect to those issues to a similar degree in which they have been emphasized by the gatekeeper (Wanta et al., 2004). For instance, if more emphasis has been put on 3 attributes related to COVID-19, such as social distancing, hand hygiene, and face covering, then the public is more likely to make links to these 3 attributes in their minds than other less highlighted attributes.

The amount of time it takes the agenda-setting effects to appear depends on how salient and important a given issue and its attributes are (McCombs & Valenzuela, 2007). Additionally, individual differences, relevance, and uncertainty are the

elements that determine the effect of agenda-setting on the public. People demonstrate strong agenda-setting effects when a public issue is relevant to them and when there is high uncertainty about it (McCombs & Valenzuela, 2007), such as during public health pandemics like COVID-19 that directly affect many aspects of people's lives.

Research on the agenda-setting effect often uses content analysis to identify the salient issues that gatekeepers focus on as part of their agenda and analyzes the public discourse to identify which issues people find most critical at any given time. Agenda-setting research then uses correlation tests to investigate how the issue and issue attributes presented by a gatekeeper (representing the gatekeeper agenda) correlate with the issue and issue attributes in the public discourse (representing the public agenda). The assumption is that if there is a positive correlation between both agendas, the gatekeeper, such as the news media, has been able to impact the public agenda (Vu et al., 2014).

Network Agenda-Setting

Guo and McCombs (2011) proposed an agenda-setting model, called network agenda-setting, according to which gatekeepers like the news media have the power to impact people's cognitive network. The news media builds "network connections" between the attributes of an issue and transfers those interconnected attributes to individuals' minds (see Figure 4). For instance, if the news media consider a country's economic problems to be associated with its foreign policy, audiences are also likely to consider them to be associated with each other (Guo & Vargo, 2015). According to network agenda-setting, "the more frequently that two elements are associated in the news coverage, the more likely it is that the audience will consider the two interconnected" (Guo & Vargo, 2015, p. 560).

Therefore, the attributes of an issue can be transferred to the public as a network of interconnected attributes. For instance, social distancing, handwashing, and

face covering, as 3 attributes related to COVID-19, which can be transferred to the public agenda simultaneously as a network of attributes (Guo & McCombs, 2011). That said, when people think about social distancing, they would also think about handwashing and face-covering as measures for protecting against the COVID-19 virus. Therefore, not only can the public be told what issues and attributes to think about and how to think about them, but they can also be told how to link those issues and attributes in their minds (Vu et al., 2014).

The main difference between the traditional agenda-setting and network agenda-setting is that the former assumes an issue and its attributes are separately and discretely transferred from the news media to the public agenda, while the latter assumes they are transferred simultaneously as a bundle of networked attributes (Guo & McCombs, 2011). Figure 4 compares the traditional and network agenda-setting models (Guo, 2012, p. 619).

Network Agenda-Setting Effect

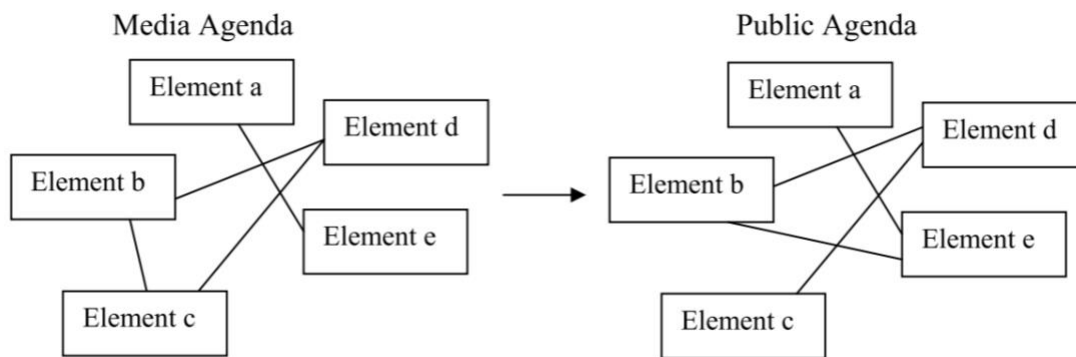
To identify the network agenda-setting effect, just as the traditional agenda-setting effect, correlation tests are used to identify how well the agenda of a gatekeeper is correlated with the public agenda. However, in network agenda-setting, the agenda will be presented in a network or co-occurrence square matrix (i.e., a matrix with the same number of rows and columns) consisting of issue attributes (see Table 5). The value in each cell in the matrix represents how many times the 2 corresponding attributes have co-occurred in a dataset. The higher the value, the stronger the 2 attributes are connected.

For instance, in Table 5, attributes 3 and 2, with a co-occurrence of 30, are connected stronger than other attributes (see Guo, 2012).

Traditional Agenda Setting Approach



Network Agenda Setting Model



Note: Elements could refer to objects, attributes, or combinations of objects and attributes.

Figure 4. The comparison of traditional agenda-setting approach and network agenda-setting model (Guo, 2012, p. 619).

Table 5. The matrix of agenda network for a hypothetical gatekeeper.

	Attribute 1	Attribute 2	Attribute 3	Attribute 4
Attribute 1		15	25	5
Attribute 2	15		30	15
Attribute 3	25	30		12
Attribute 4	5	15	12	

Therefore, a matrix represents the agenda network of a gatekeeper or the public for a given issue in a specific period (Vu et al., 2014). Assessing the correlation between the 2 matrices can determine if the former has any agenda-setting effect on the latter (Guo, 2012).

In network agenda-setting studies, social network analysis is applied to illustrate how issue attributes are interrelated (Guo, 2012). In a network that demonstrates an agenda, each node represents an attribute of an issue, and each tie between any 2 nodes represents their relationships. The number of times the 2 attributes co-occur in a dataset represents the strength of the tie (Guo, 2017).

Network analysis has been widely used in social science in different contexts, such as economics, health, and social and behavioral sciences, to study social structures (Wasserman & Faust, 1994). Network agenda-setting studies also use network analysis (Chen et al., 2019; Guo & McCombs, 2011; Guo & Vargo, 2015; Vu et al., 2014; Yüksel & Dingin, 2020). For instance, Cheng (2016) showed a significant positive correlation between the media agenda network and the public agenda network in Hong Kong. Vu et al. (2014) found a significant correlation between the media agenda network and the public agenda network, confirming that the news media made a network of related issues salient in people's minds (Vu et al., 2014).

Agenda-setting on Social Media

Social media are the main platforms for public conversations on issues such as social, political, environmental, and health issues. Like the news media, social media can significantly affect public opinion on these issues (Moy & Bosch, 2013). Social media also play an increasingly significant role in agenda-setting (Yang et al., 2016) by making large-scale communication possible and giving voice to people, such as minorities (Boynton & Richardson Jr, 2016). The increasing adoption of social media has changed how the news media, politicians, and other

influential actors communicate with people and perform their agenda-setting activities (Yang et al., 2016). For instance, during elections, candidates and their campaigns make strategic use of social media to mobilize voters by bringing their attention to the issues that are of great public concern (Skogerbø & Krumsvik, 2015).

Hemsley (2019) stated that the strategic use of social media such as Twitter and its features such as hashtags could establish and promote health, social, political, or environmental agendas. Hashtags and the stories that form around them can become part of people's social reality and inform their worldviews (Hemsley, 2019). For instance, Twitter and hashtags can be used to enhance information dissemination, publicize the movement, invite new people to the movement, enhance its visibility, broadcast messages to broader audiences, and attract people's attention (Potnis & Tahamtan, 2021; Wang et al., 2016).

Lee and Xu (2018) also noted that Twitter could be used during elections to set public agendas. For instance, Donald Trump used Twitter and hashtags during the 2016 U.S. presidential election to develop a variety of public agendas, most importantly, the "media bias" and "Clinton's alleged dishonesty". Lee and Xu (2018) showed that Donald Trump was more successful than Hillary Clinton in drawing public attention to the agendas highlighted by his campaign on Twitter. Feezell (2018) indicated that being exposed to political information on Facebook increased perceived issue salience and importance, yielding an agenda-setting effect.

The Gap in Network Agenda-Setting Literature

Agenda-setting has been mostly studied within the context of political sciences (e.g., Conway et al., 2015; Feezell, 2018) while it is less studied in the health context, specifically on social media. More specifically, it is understudied how

public health actors such as WHO set an agenda on social media during pandemics and what impact it has on different categories of social media users.

Studies have suggested that agenda-setting can have different effects on subgroups in public in the offline world (Blinder & Krueger, 2004; Guo, 2017; McCombs & Valenzuela, 2007). The effect of agenda-setting on different categories of social media users is not studied enough. More specifically, network agenda-setting model does not focus on how different categories of social media users are affected by the gatekeepers they follow on social media. This study fills in these gaps in the literature.

METHODOLOGY

Classifying WHO Followers on Twitter to 6 User Categories

WHO followers on Twitter were classified into 6 categories, including (a) healthcare professionals, (b) academics, (c) politicians, (d) print and electronic media, (e) legal professionals, and (f) the private sector. This classification was done to investigate if and how different categories on social media react to a public health issue.

We adopted and modified the approach used by Toupin et al. (2019) to classify Twitter users. The main reason for selecting these categories is that they are influential actors in society whose actions can impact citizens during crisis events as explained in the following paragraphs.

In this study, healthcare professionals include public health workers in academia and industry sectors, such as doctors and nurses. Healthcare professionals serve citizens during public health emergencies in various ways, for instance, by warning them against self-medicating (Hedima et al., 2021).

In this study, academics were defined as the people who work in academia (except healthcare professionals), such as professors, researchers, and students who can

inform society through their research and writing about various issues related to the COVID-19 pandemic (Laufer, 2021).

Politicians include policy and decision-makers in the state and federal governments, such as mayors, congressmen, congresswomen, and senators. Politicians can impact people by, for instance, communicating with them about the concerns raised around vaccine safety (Engel-Rebitzer et al., 2021).

Electronic and print media include those responsible for information dissemination and public awareness, such as journalists, press, news agencies, and publishers. The print and electronic media are powerful sources of information for the public as a crisis unfolds (Gruber et al., 2015). They can, for example, fact-check the information shared on social media related to COVID-19 (Luengo & García-Marín, 2020).

Legal professionals include courts, lawyers, and attorneys who provide legal advice and resources, for instance, for an ideal crisis-communication strategy (Perry et al., 2003). They can ensure the compliance of policies with national laws such as human rights (Drennan et al., 2012).

Private sectors include corporations, incorporated organizations, companies, chief executive officers, and for-profits who serve society by satisfying the needs of citizens. For example, companies can take necessary actions to serve their customers by empowering their employees to operate remotely (Agrawal et al., 2020).

The classification of followers into 6 categories was done according to the short biographical profiles of Twitter users. R software was used to collect and analyze the biographies of Twitter users according to the following steps:

First, the I.D. of the approximately 7.5 million Twitter accounts following WHO in 2020 were retrieved using the *get_followers* function in the *rtweet* package. After

that, the “username” associated with each I.D. was collected using the *lookup_users* function in the *rtweet* package.

Next, the “description” used in biographies of the accounts (i.e., usernames) were collected using the *users_data* function in the *rtweet* package. Table 17 in the Appendix provides a list of keywords used to classify and identify the Twitter user categories. The list was generated by searching on the Internet and using websites such as the US Bureau of Labor Statistics (2021) that provide a list of job titles in various domains. For instance, the keywords used to identify “academics” were as follows: “lecturer,” “professor,” “phd,” “student,” “ph.d.,” “postdoc,” “postdoctoral,” “doctoral,” “msc,” “master,” “ms,” “bs,” “bachelor,” “undergrad,” “grad,” “graduate,” “undergraduate,” “scientist,” “postgrad,” “faculty,” “chancellor,” “university,” “college,” “school,” “provost,” and “vice-provost.”

To make each category as exclusive as possible and increase the reliability of the classification, general keywords, such as “research,” “researching,” “teams,” “organizations,” “institutes,” “campus,” “professional,” “officer,” “change,” “equity,” and “policy,” were excluded in classifying Twitter users.

The preliminary investigation and analysis of users’ biographies indicated that some keywords such as “chief” or “boss” appeared in several categories. Such keywords were also excluded.

Data Collection

Collecting WHO Tweets

Twitter was the main source for data collection. Twitter contains features such as hashtags, retweets, replies, mentions, and likes that make it a suitable platform for studying online social interactions (Wasike, 2013). Using the *brandwach* platform, the current study collected 7,090 tweets posted by WHO from January 1, 2020, to July 31, 2020.

Collecting Tweets for the 6 Twitter user categories

The tweets related to COVID-19 posted by each Twitter user category from January 1, 2020, to July 31, 2020, were collected by using the *get_timeline* function from the *rtweet* package.

Data Cleaning

Removing Bots

Previous studies have shown that bot accounts are active on Twitter, specifically during political debates, social movements, and public health emergencies. For instance, Ferrara (2020) indicated that bots actively promoted political conspiracies during the COVID-19 pandemic. The current study used the fast model of the *tweetbotornot* package in R software to classify Twitter accounts into bots and non-bots. This model uses the user-level data (bio, location, number of followers and friends, etc.) to estimate the probability that users are bots (Kearney, 2019). It is 91.78% accurate in identifying bots and 92.61% accurate in identifying non-bots. This method classifies 90,000 Twitter users as bots or non-bots every 15 minutes (Kearney, 2019). Accounts that receive a score of at least 50%, or a probability of 0.5, are bots and should be removed (Davis et al., 2016). Of the 656,805 Twitter accounts in the dataset, 441,041 (i.e., 67%) usernames were classified as bots and excluded from the analysis.

Removing Non-English and Non-COVID-19 Tweets

Non-English and non-COVID-19 tweets were removed from both the WHO and WHO followers datasets.

Overall, 7,965,610 tweets written in non-English languages were removed from the dataset of WHO followers, leaving 7,547,019 (48.65%) tweets in the dataset written in English (see Table 6).

The initial investigation of the tweets indicated that many of the tweets posted by WHO and Twitter user categories were irrelevant to COVID-19. For instance, WHO had posted many tweets about Ebola, opioids, cancer, tobacco, malaria, or nurses and midwives, all irrelevant to COVID-19. Only the tweets that contained COVID-19 related keywords and hashtags (identified by manual inspection of the WHO dataset) were included in the study. Additionally, this study investigated the top keywords and hashtags in the WHO dataset and selected those relevant to COVID-19. For a list of such terms, see A1 in the Appendix. This approach removed 2,111 (i.e., 29.77%) of the tweets, leaving 4,979 tweets in the dataset.

Using a similar approach, the tweets posted by the 6 Twitter user categories that contained at least a keyword or hashtag (listed in A2 in the Appendix) such as #covid, pandemic, #coronaupdates, or #novelcoronavirus were included in the analysis. The final dataset included 918,976 (i.e., 5.9%) tweets related to COVID-19 and written in English (see Table 6).

Content Analysis to Identify WHO Agenda

Content analysis was used to identify the main topics (i.e., issues) discussed by WHO in the first half of 2020. The issues constitute WHO agenda related to COVID-19 on Twitter. An agenda is the issues presented in the public or media or any other medium at a given time (Christie, 2006).

The tweets posted by WHO (n=7090) were stratified by months (January, February, March, April, May, June, and July in 2020) in Microsoft Excel. Using stratified sampling, 10% (n=709) of WHO tweets were randomly selected. The sample size for each stratum (i.e., month) was proportional to the number of tweets in the stratum (Krippendorff, 2018), as indicated in Table 7.

Table 6. Twitter user categories and their COVID-19 related tweets in English from January 1 to July 31, 2020.

	Twitter user accounts	Frequency of Bot accounts removed	Frequency of tweets by non bot accounts	Frequency of tweets written in English	Frequency of tweets written in English related to COVID-19
A	23,6494	17,0443	3,752,817	2,513,946	296,431
P	39,259	24,358	804,296	595,710	66,132
PEM	162,934	96,804	2,720,268	2,082,200	197,522
H	125,572	93,380	6,953,100	1,404,590	237,166
L	39,244	24,745	545,844	380,043	54,493
PS	53,302	31,311	736,304	570,530	67,232
All	656,805	44,1041	15,512,629	7,547,019	918,976

A = Academics, P = Politicians, PEM = Print and electronic media, H = Healthcare professionals, L = Legal professionals, PS = Private sector.

The content analysis was carried out in 3 steps:

First, in the training phase, the 2 coders were trained to familiarize themselves with the content being analyzed (Riffe et al., 2019). The familiarization process included the 2 coders coding a set of randomly selected tweets together inductively to increase “coders” comfort level with the content of interest, to give them an idea of what to expect in the content, and to determine how much energy and attention is needed to comprehend it” (Riffe et al., 2019, p. 106). The 2 coders assessed the intercoder reliability informally, with about 50 tweets that were not part of the sample to be coded (Lombard et al., 2002).

Discrepancies were discussed between the 2 coders to come to the same understanding of how the tweets should be coded. For instance, once a given tweet was coded differently, the coders explained their thought process for coding the tweet, discussed their rationale, and agreed upon how similar tweets in the dataset should be coded. This helped the coders refine the coding instructions until they reached an adequate level of agreement.

The second phase, called the pilot test, included coders coding the tweets again and assessing the intercoder reliability independently. The coders coded 100 of the tweets from a separate representative sample from the WHO dataset that was selected by the stratified sampling method (Lombard et al., 2002). This resulted in an 80% intercoder reliability agreement.

The third and final step included coding the total sample size (see Table 7) independently. The final intercoder reliability agreement was 85%.

The coding in the training phase, pilot test, and final analysis was done by assigning to each tweet 1 to 3 keywords that described the tweet's content. For example, “handwash” and “handrub” were the 2 keywords assigned to a tweet by WHO (2020) that is demonstrated in Figure 5.

Table 7. Sample size of WHO tweets.

The months when the tweets were posted by WHO	Frequency of tweets	Proportion of tweets in the final sample (10% of the population)
January 2020	816	82
February 2020	1,350	135
March 2020	1,287	129
April 2020	1,402	140
May 2020	1320	132
June 2020	915	92
Total	7,090	709



World Health Organization (WHO) Western ...



Feb 1, 2020



How to handwash?

Use 🍷 and water for at least 40-60 seconds

How to handrub?

Use alcohol-based handrub 🧴 for 20-30 seconds

#coronavirus

How to Handrub?

RUB HANDS FOR HAND HYGIENE! WASH HANDS WHEN VISIBLY SOILED

⌚ Duration of the entire procedure: 20-30 seconds

1. Apply a palmful of the product in a cupped hand, covering all surfaces;

1b. Rub hands palm to palm;

2. Rub hands palm to palm;

3. Right palm over left dorsum with interlaced fingers and vice versa;

4. Palm to palm with fingers interlaced;

5. Backs of fingers to opposing palms with fingers interlaced;

6. Rotational rubbing of left thumb clasped in right palm and vice versa;

7. Rotational rubbing, backwards and forwards with clasped fingers of right hand in left palm and vice versa;

8. Once dry, your hands are safe.

How to Handwash?

WASH HANDS WHEN VISIBLY SOILED! OTHERWISE, USE HANDRUB

⌚ Duration of the entire procedure: 40-60 seconds

0. Wet hands with water;

1. Apply enough soap to cover all hand surfaces;

2. Rub hands palm to palm;

3. Right palm over left dorsum with interlaced fingers and vice versa;

4. Palm to palm with fingers interlaced;

5. Backs of fingers to opposing palms with fingers interlaced;

6. Rotational rubbing of left thumb clasped in right palm and vice versa;

7. Rotational rubbing, backwards and forwards with clasped fingers of right hand in left palm and vice versa;

8. Rinse hands with water;

9. Dry hands thoroughly

10. Use towel to turn off faucet;

11. Your hands are now safe.

28

1.4K

1.2K



Figure 5. A tweet by WHO about hand washing and hand rubbing posted on February 01, 2020.

In classifying keywords into different categories (i.e., issues promoted by WHO on Twitter), the context of the tweets was taken into consideration. The keywords that appeared in more than one issue or those not contextually meaningful were removed. For instance, “support” was removed because it appeared in 3 categories (i.e., Issues). Each issue was identified by a set of exclusive keywords and hashtags (see Table 18 in the Appendix).

For instance, as Table 18 indicates, “credibility” was a main category that included facts, fact, rumors, misinformation, #knowthefact, #knowthefacts, and #takecarebeforeyoushare. Another example is “solidarity” that included #UnitedAgainstCoronavirus, #WithRefugees, compassion, help, humanitarian, kindness, resilience, solidarity, and unity.

This study ensured the keywords within each issue were representative of that issue by several rounds of discussions among researchers.

Eventually, the content analysis resulted in identifying 7 issues (see Table 18) in the WHO tweets related to the COVID-19 pandemic, including “prevention,” “solidarity,” “charity,” “teamwork,” “ill-effect,” “surveillance,” and “credibility.” These issues are the attributes of COVID-19 and constitute the WHO agenda in the first half of 2020. Thereafter, the frequency of these issues in the entire WHO dataset was calculated.

Constructing Co-occurrence Matrices and Networks

A major objective of this study was to assess the correlation between the WHO agenda network and the agenda network of each Twitter user category. This is the main goal in network agenda-setting studies (Guo, 2017; Guo & McCombs, 2011; Vargo et al., 2014).

Following the literature (e.g., Guo, 2012; Vargo et al., 2014), a co-occurrence matrix was created for each of the 7 issues for WHO and each Twitter user

category. Each matrix included 7 columns and 7 rows. Each row and column represent an issue related to COVID-19. Each cell contains a digit representing how many times the 2 issues have co-occurred in the dataset of tweets. For example, the cell associated with “teamwork” and “charity” in the WHO matrix is 51, which means that they were mentioned 51 times together by WHO on Twitter in the first half of 2020 (i.e., the period investigated in this study). Similarly, the cell that corresponds to “solidarity” and “prevention” is 150 in the WHO dataset, meaning these 2 issues have co-occurred 150 times. The number of times the 2 issues co-occur in a dataset represents the strength of the tie between those issues (Guo, 2017). Table 11 in the results section demonstrates the co-occurrence matrix for WHO followers on Twitter. All other matrices are presented in Tables 19 to 24 in the Appendix.

The matrices were used to create the WHO agenda network and agenda network for each Twitter user category. Networks were created by using text mining and network analysis techniques via the *quanteda* library in the R software. The networks associated with the matrices are presented in Figure 6 to 13 in the Appendix.

Quadratic Assignment Procedure (QAP)

Quadratic assignment procedure (QAP) was used to assess the correlation between WHO agenda network (i.e., matrix) and the agenda network of each Twitter user category. QAP is a commonly used statistical test in social network analysis and network agenda-setting studies (e.g., Vargo et al., 2014; Yüksel & Dingin, 2020) to calculate the Pearson’s correlation coefficient between 2 matrices (Vu et al., 2014). QAP indicates whether the correlation between 2 matrices or networks is statistically significant or not. Once the 2 matrices are significantly correlated, QAP regression can be used to assess whether an independent variable can predict a dependent variable (Guo, 2012). QAP linear regression was

used to assess if the WHO agenda network could predict the agenda network of Twitter user categories.

In this study, Granger causality was used, for instance, to examine if “credibility” as an issue that was promoted by WHO on Twitter predicted the future values of “credibility” in the tweets posted by WHO followers. If the p-value of a Granger causality test is less than 0.05, the independent variable is said to Granger cause or predict the value of the dependent variable (Tan & Weaver, 2007). For instance, it can be said Y Granger caused the values of X. However, it is important to note that Granger causality does not mean causation. In the Results and Discussion sections of this study, the term “influenced” will be used instead of “Granger caused”.

To investigate if each time series in WHO (e.g., teamwork) could predict the value of its corresponding time series (i.e., teamwork) in any of the Twitter user categories, a VAR model was created. Additionally, to investigate if each time series in any of the Twitter user categories (e.g., teamwork) could predict the value of its corresponding time series (i.e., teamwork) in WHO, VAR models were created. Overall, 98 VAR models were created in this study.

To perform Granger causality, first, each variable (i.e., issue) should be treated as a time series (Vargo & Guo, 2017). This study created time series for each of the 7 issues in the WHO dataset and 6 Twitter user categories, as explained in the following section.

Creating Time Series

To create time series for each issue, the frequency of it was calculated over time from January 1 to July 31, 2020, for both WHO and Twitter user categories. For each issue, a time series with 182 records was created. Each record contained the frequency of the issue on a specific date. The initial analysis indicated that each time series had many zero number values, that resulted in making the data

skewed. Each zero number represents a lack of data for a given issue on a given date. The highly skewed data violated the normality assumption (see below, Testing the Residual Normality).

Additionally, having a wide range of values from zero to several hundred led to violating the heteroscedasticity assumption (see below, testing the residual heteroskedasticity) in many cases. This study tried to resolve the normality and heteroscedasticity issues by aggregating the data to weekly data to reduce zeros. Therefore, for each issue, a time series of 26 weeks was created. Although the data was aggregated to weekly data, it was found that the first 2 weeks for most issues still included zero numbers which again violated the normality assumption in some cases. Removing the first 2 weeks of June 2020 from the analysis resolved the normality issue. Therefore, the analysis was carried out on times series with 24 records (i.e., weeks). As an example, the times series for the issues of WHO followers (i.e., all 6 Twitter user categories together) are presented in Table 8 below.

To perform Granger causality, vector autoregressive models should be created first, as explained below.

Vector Autoregressive (VAR) Model

A VAR model is used to determine how 2 or more times series influence each other. In a VAR model, each time series is modeled as a linear combination of past values of itself and the past values of other variables (Rossi & Wang, 2019). For instance, a VAR model can be used to determine the relationship between the “team-work” time series in WHO (TW) and the “team-work” time series in one of the Twitter user categories (TU) at time (t). Since there are 2 time series, 2 VAR models should be created, one for TW and one for TU. The VAR model for TW uses the past values of itself (TW) and the past values of the other variable (TU). In its simple form, the VAR model for TW and TU can be as follows, where TW_{t-1}

and TW_{t-2} are the first and second lags of TW (first variable) and $TU_{t-1} + TU_{t-2}$ are the first and second lags of TU (second variable). Each lag is x period ago. For instance, lag one is one time period ago or lag two is 2 time periods ago.

$$TW = TW_{t-1} + TU_{t-1} + TW_{t-2} + TU_{t-2}$$

$$TU = TU_{t-1} + TW_{t-1} + TU_{t-2} + TW_{t-2}$$

In a VAR model a different number of lags can be considered for each variable. Thus, the optimal number of lags should be selected using a criterion. This study used Akaike's information criterion to select the optimal lag for each VAR model, explained below.

Lag Selection

The most commonly used criterion in lag selection in VAR models is Akaike's Information Criterion (AIC) (Ivanov & Kilian, 2005; Liew, 2004). AIC specifies the number of lags to be used in a VAR model (Liew, 2004).

Testing the Stationary Nature

A major assumption underlying the VAR model and Granger causality is that time series must be stationary (Granger, 1969), otherwise, they should be made stationary using the first or higher differences of the variables. A stationary time series has no systematic trend, meaning that its mean and variance do not change over time (Chatfield & Xing, 2019). Non-stationary times series lead to incorrect inferences (Rossi & Wang, 2019). The Augmented Dickey-Fuller Test was used to test whether the variables were stationary (Dickey & Fuller, 1979). A time series is stationary if the p-value of the Augmented Dickey-Fuller test is less than 0.05. In this study, all variables in the WHO dataset and datasets of the 6 Twitter user categories were non-stationary, which were transformed to become stationary through differencing (first or higher differences of the variables). Differencing is the process in which the differences between consecutive observations of a variable (i.e., time series) are computed (Bessler & Kling, 1984).

Table 8. Time series for the 7 issues of WHO followers.

Week	T	Ch	Su	P	So	Ill	Cr
3	4	0	25	78	4	1	1
4	87	23	142	1043	111	6	51
5	99	33	154	1360	266	24	213
6	54	41	56	696	187	14	83
7	115	34	55	657	191	22	80
8	170	42	90	676	118	44	91
9	316	157	294	4625	650	91	293
10	482	226	376	7448	1256	128	450
11	1961	1262	1171	22419	6107	717	1248
12	2065	3427	1162	30776	10397	1054	1311
13	2535	3892	1075	26190	9351	1407	1862
14	2272	2833	1004	19813	7282	1531	1004
15	1927	2315	930	14484	5759	1051	612
16	1802	3551	936	13808	5185	1122	736
17	1486	2067	895	12095	4175	977	473
18	1211	1901	787	11312	3697	857	728
19	1202	1169	770	8492	2970	852	337
20	1208	1259	680	9257	2872	919	350
21	922	942	610	7596	2308	716	358
22	972	812	631	7059	2099	910	316
23	756	776	495	6830	1823	680	309
24	770	727	514	7057	1813	837	282
25	742	732	480	7295	2063	718	281
26	721	656	421	7672	1,523	476	266

T = Teamwork, Ch= Charity, Su = Surveillance, P = Prevention, So = Solidarity,
 Ill-effect = Ill, Cr = Credibility

Testing the Residual Autocorrelation

A VAR model should be tested to determine if it “provides an adequate description of the data. ... In time series models, autocorrelation of the residual values is used to determine the goodness of fit of the model. Autocorrelation of the residuals indicates that there is information that has not been accounted for in the model” (Bose et al., 2017, p. 7). The Portmanteau test was used to check the presence of autocorrelation in the models. If the resulting p-value in this test is less than 0.05, autocorrelation exists.

Testing the Residual Normality

Another assumption underlying the VAR model is that its residuals should be normally distributed, otherwise inferences may be incorrect. The normality of residuals for all models was tested using the multivariate Jarque-Bera test. After performing this test, when the resulting p-value is larger than 0.05, the residuals of VAR model are normal. In 4 cases, BoxCox transformation was used to make the VAR model normal (see Tables 27 and 29 in the Appendix).

Testing the Residual Heteroscedasticity

Another assumption underlying the VAR model is that there should be no heteroscedasticity in residuals. Heteroscedasticity refers to a condition in which the variance of the residual in a regression model varies widely. To test heteroscedasticity, the ARCH-LM test (ARCH refers to Multivariate Autoregressive Conditional Heteroscedastic) proposed by Engle (1982) was used. Once the test is performed, if the resulting p-value is larger than 0.05, there is no heteroscedasticity in the data. No heteroscedasticity was observed in the VAR models.

RESULTS

Results of Content Analysis

The first study objective was to identify the WHO agenda about the COVID-19 pandemic. Using content analysis, 7 issues that constituted the WHO agenda were identified inductively, including prevention (2,430) followed by solidarity (717), teamwork (601), surveillance (276), charity (243), ill-effect (213), and credibility (156). The numbers in the parentheses represent the frequency of each issue. The description of each issue is presented in the following section. Table 9 indicates the keywords associated with each issue.

“Prevention” refers to the tweets posted by WHO about how to avoid contracting the virus, including content about disinfecting surfaces, hand washing, wearing masks, vaccination, social distancing, isolation, and staying home.

“Solidarity” refers to the tweets emphasizing the importance of unity, resilience, kindness, or supporting groups like refugees.

“Teamwork” was another issue discussed by WHO in the first half of 2020 to highlight that countries, governments, organizations, and people should collaborate, coordinate, cooperate, be committed, and be accountable to control the pandemic.

“Surveillance” emphasizes that governments should keep tracing, investigating, monitoring, and screening people and regions affected by the virus to take necessary actions.

“Charity” refers to the donations, fundraisings, and financial support received by WHO from governments, organizations, companies, celebrities to fight against the virus.

“Ill-effect” refers to WHO tweets about the consequences of the virus, such as disruptions in the economy, trades, health systems, mental health, abuse, and home violence during the quarantine.

“Credibility” includes the tweets that demonstrate the importance of facts and bring people’s attention to the rumors, misinformation, and fake information related to COVID-19.

This study also calculated the frequency of these issues for the 6 Twitter user categories and all of them together (hereafter, WHO followers). In the dataset of WHO followers, prevention (228,700) had the highest frequency, followed by solidarity (72,192), charity (28,870), teamwork (23,879), ill-effect (15,151), surveillance (13,761), and credibility (11,726). Table 10 presents the frequency of these issues in the WHO dataset, WHO followers dataset, and the dataset of each Twitter user category. The WHO followers dataset refers to the tweets posted by the 6 Twitter user categories altogether.

Each of these issues co-existed with other issues on social media. For instance, there was a strong tie between “prevention” and “solidarity” in most networks, such as the private sector dataset (see Table 19 and Figure 9 in the Appendix). The connections between the 6 issues in WHO agenda network may indicate that WHO “connect[s] and relate[s] issues together to construct social realities” (Vargo & Guo, 2017, p. 1047), and these social realities can transfer to the public’s mind through network agenda-setting.

The strong tie between “solidarity” and “prevention” could indicate that the former is vital for the prevention of COVID-19 (or even treatment and response to the virus). For instance, to help prevent the spread of the virus, people should be united in complying with public health guidelines such as staying home, hand washing, and social distancing.

Table 9. The keywords representing each of the 7 issues promoted by WHO on Twitter.

Issues	Frequency	Keywords associated with each issue
Prevention	2430	Disinfecting surfaces, hand washing, wearing masks, vaccination, social distancing, isolation, and staying home.
Solidarity	717	Unity, resilience, kindness, supporting groups like refugees.
Teamwork	601	Collaboration, coordination, cooperation, being committed, and being accountable.

Table 9 continued.

Issues	Frequency	Keywords associated with each issue
Surveillance	276	Tracing, investigating, monitoring, and screening people and regions affected by the virus to take necessary actions.
Charity	243	Donations, fundraisings, and financial support received by WHO from governments, organizations, companies, and celebrities.
Ill-effect	213	Consequences of the virus such as disruptions in the economy, trades, health systems, mental health, abuse, and home violence during the quarantine.
Credibility	156	Tweets about facts, rumors, misinformation, and fake information related to COVID-19

Table 10. Frequency of issues in the datasets of WHO, WHO followers, and each Twitter user category.

	WHO	WHOF	H	A	P	PEM	L	PS
P	2430	228700	62414	72318	17519	46921	12905	16623
So	717	72192	18269	23500	6913	12758	4286	6466
T	601	23879	5403	7802	3267	3785	1518	2104
Su	276	13761	4110	4443	929	2419	725	1135
Ch	243	28870	5522	9417	3131	5783	2046	2971
ill	213	15151	3348	5160	1400	2794	1282	1167
Cr	156	11726	3142	3766	835	2567	718	698

WHO Followers (WHOF) which constitutes all 6 Twitter user categories following WHO on Twitter. H = Healthcare professionals, A = Academics, P = Politicians, PEM = Print and electronic media, L = Legal professionals, PS = Private sector.

P = Prevention, So = Solidarity, T = Teamwork, Su = Surveillance, Ch= Charity, Ill-effect = Ill, Cr = Credibility.

Results of QAP

QAP was used to measure the similarity between agenda networks (matrices). QAP calculates the Pearson's correlation coefficient between the 2 matrices. The co-occurrence matrices for WHO and WHO followers are presented in Table 11 and Table 12. These 2 matrices show that the strongest tie has been between "solidarity" and "prevention" in the matrix of WHO and WHO followers. "Solidarity" and "prevention" also had the strongest tie in the matrix of all 6 Twitter user categories. Other matrices are presented in Tables 19 to 24 in the Appendix.

The results of QAP tests indicated a positive and high correlation between WHO agenda network and the agenda network of WHO followers (see Table 13). The QAP correlation tests also showed that the WHO agenda network and the agenda network of the 6 Twitter user categories were significantly correlated, proving the network agenda-setting model in that the salience of networked attributes of COVID-19 can be transferred from WHO to the public. Therefore, WHO can make a network of interconnected COVID-19 attributes prominent in the public's mind simultaneously, as suggested by the network agenda-setting model (Guo & McCombs, 2011).

Results of QAP Regression

QAP linear regression was carried out to assess whether the independent variable (WHO agenda network) could predict the dependent variables (the agenda networks of the 6 Twitter user categories). As indicated in Table 14, WHO agenda network could predict all dependent variables, proving further evidence that the agenda network of WHO can impact the agenda network of Twitter user categories. Adjusted R-squared values indicate whether the WHO agenda network is the main factor in forming issue ties in Twitter user categories. For instance, the adjusted R-squared for the politicians Twitter user category is 0.71, representing

that WHO can possibly explain 71% of the variance in the politicians agenda network.

Table 14 indicates that WHO also explains 63% of the variance in the legal professionals network, 62% of the variance in academics network, 61% of the variance in the private sector network, 60% of the variance in the healthcare professionals network, and 59% of the variance in the print and electronic media network. WHO also explains 62% of the variance in the network of WHO followers.

Results of Granger Causality

By performing 98 Granger causality tests, this study examined if the 7 issues in the WHO agenda Granger caused or predicted the future values of the issues in the tweets by the 6 types of Twitter users or vice versa. For instance, it was tested to see if “teamwork” in WHO Granger caused (i.e., predicted the future values of) “teamwork” in healthcare professionals. It was also investigated if “teamwork” in healthcare professionals Granger caused “teamwork” in WHO. This study uses the term “influenced” instead of “Granger caused” or “predicted the value of”.

Tables 15 and 16 provide summaries of Granger causality tests for WHO and WHO followers. The summary of the Granger causality tests for other Twitter user categories are presented in Tables 25 to 30 in the Appendix. Among the 7 issues, only “surveillance” in WHO influenced “surveillance” in WHO followers ($F_{5,10}=4.74$, $P=.01$). On the other hand, among the 7 issues in WHO followers, “charity” influenced “charity” in WHO ($F_{6,6}=7.48$, $P=.01$), and “prevention” influenced “prevention” in WHO ($F_{5,10}=4.69$, $P=.01$).

The results indicated that WHO influenced “surveillance” in politicians ($F_{6,6}=5.13$, $P=.03$) and “surveillance” in print and electronic media ($F_{5,10}=9.33$, $P=.001$). Additionally, WHO influenced “ill-effect” in print and electronic media ($F_{5,10}=4.02$, $P=.02$), “credibility” in the private sector ($F_{5,10}=7.12$, $P=.001$), and “credibility” in academics ($F_{5,10}=12.5$, $P=.001$).

Table 11. The matrix of issues in the WHO dataset on Twitter.

	T	Ch	Su	P	So	Ill	Cr
T		51	23	110	118	9	6
Ch	51		1	37	90	3	2
Su	23	1		101	14	2	0
P	110	37	101		150	48	37
So	118	90	14	150		28	20
Ill	9	3	2	48	28		3
Cr	6	2	0	37	20	3	

T = Teamwork, Ch= Charity, Su = Surveillance, P = Prevention, So = Solidarity, Ill-effect = Ill, Cr = Credibility.

Table 12. The matrix of issues in the dataset of WHO followers on Twitter.

	T	Ch	Su	P	So	Ill	Cr
T		1303	331	3041	2390	307	208
Ch	1303		141	4159	4838	332	86
Su	331	141		2849	856	85	82
P	3041	4159	2849		13132	2502	2136
So	2390	4838	856	13132		1425	682
Ill	307	332	85	2502	1425		84
Cr	208	86	82	2136	682	84	

T = Teamwork, Ch= Charity, Su = Surveillance, P = Prevention, So = Solidarity, Ill-effect = Ill, Cr = Credibility.

Table 13. The QAP correlations between WHO agenda network, and the agenda network of WHO followers and 6 Twitter user categories.

Twitter user categories	Correlation (r) with the WHO agenda matrix	P-value
Politicians	0.85	0.001
Private sector	0.79	0.01
Print and electronic media	0.77	0.01
Legal professionals	0.80	0.01
Healthcare professionals	0.79	0.001
Academics	0.79	0.01
WHO followers	0.80	0.01

Table 14. QAP linear regression for WHO agenda network (independent variable) and the networks of Twitter user categories (dependent variables)

Dependent variables	F-statistic	Coefficient	Adjusted R-squared	p-value (two_tailed)
Politicians	104.9	5.8	0.71	0.002
Private sector	66.22	4.9	0.61	0.005
Print and electronic media	60.43	9.5	0.59	0.008
Legal professionals	71.95	3.2	0.63	0.005
Healthcare professionals	61.7	13.6	0.60	0.001
Academics	67.89	17.0	0.62	0.004
WHO followers	70.01	51.2	0.62	0.001

Table 15. Granger causality test for WHO issues as independent variables and the issues in WHO followers as dependent variables.

Issues	F-Test	P-value
Teamwork	0.04	0.99
Charity	0.31	0.91
Surveillance	4.74	0.01
Prevention	0.27	0.92
Solidarity	0.16	0.97
Ill-effect	1.49	0.29
Credibility	2.57	0.11

Table 16. Granger causality test for the issues in WHO followers as independent variables and WHO issues as dependent variables.

Issues	F-Test	P-value
Teamwork	0.49	0.78
Charity	7.48	0.01
Surveillance	1.70	0.22
Prevention	4.69	0.01
Solidarity	0.93	0.50
Ill-effect	0.66	0.66
Credibility	1.23	0.38

Twitter user categories also influenced several topics in the WHO agenda: “credibility” in academics ($F_{5,10}=6.10$, $P=.001$), “credibility” in politicians ($F_{5,8}=8.06$, $P=.001$), and “credibility” in the private sector influenced “credibility” in the WHO ($F_{5,10}=4.33$, $P=.02$).

“Charity” in health care professionals ($F_{6,6}=37.93$, $P=.001$) and “charity” in academics influenced “charity” in the WHO ($F_{6,6}=4.62$, $P=.04$). “Prevention” in politicians ($F_{5,10}=13.21$, $P=.001$) and “prevention” in print and electronic media ($F_{5,10}=15.04$, $P=.001$) influenced “prevention” in the WHO. Print and electronic media influenced “surveillance” ($F_{5,10}=3.7$, $P=.04$) in the WHO. The private sector also influenced “ill-effect” in the WHO ($F_{5,10}=7.35$, $P=.001$). It was found that WHO and legal professionals did not influence each other in any of the 7 issues.

DISCUSSION

Rarely any previous study has investigated the network agenda-setting effects of a gatekeeper on various categories of social media users, specifically in the context of public health emergencies. This study made the first attempt to fill this gap by exploring the relationship between the agenda network of WHO and 6 Twitter user categories following WHO on Twitter, regarding the COVID-19 pandemic in the first half of 2020.

CONTRIBUTION TO AGENDA-SETTING

Who sets the agenda first?

This study found that, although there was a high correlation between the WHO agenda network and agenda network of Twitter user categories, WHO influenced only some issues related to COVID-19 in the 6 Twitter user categories and vice versa (see the Granger causality test results). For instance, WHO only influenced “ill-effect” in print and electronic media. Likewise, different Twitter user categories influenced only some (not all) issues in the WHO agenda.

It is hard to say who is leading the overall trends and topics related to COVID-19 on Twitter, mainly because social media provide unlimited space where various sources can interact with and impact each other (see, Vu et al., 2014). However, it seems that there is less interaction between WHO and some Twitter user categories during public health emergencies. For instance, neither legal professionals nor WHO influenced each other. It is possible that legal professionals are not influenced by the WHO because they naturally often perform independently and remain impartial of external resources.

This study was not designed to measure the impact of WHO on top influencers within each Twitter user category or vice versa. Future research can explore who sets the agenda and who establishes the agenda-setting effect first. One hypothesis that should be studied further is that WHO originates the tweets about COVID-19, but the top influencers within each category of WHO followers on Twitter set the agenda or promote the agenda already set by WHO, through retweeting the WHO tweets.

Two-way Agenda-Setting Effects

This study informs the network agenda-setting model by demonstrating that there can be a “two-way” agenda-setting effects on social media, where WHO and various categories of social media users influence each other’s agenda. Vargo and Guo (2017) also stated that the media agenda is reciprocal, in that network agenda setting is more complex than what past traditional agenda-setting studies have suggested.

Evaluating the network agenda-setting effects on social media is more complex than other platforms because, for instance, the agenda of WHO followers about COVID-19 could have been influenced by other resources too, such as CDC, providing initial evidence for “multidirectional” or “multiway” network agenda setting effects.

Thus, WHO does not seem to set the public agenda in a unidirectional nature. Neither WHO nor Twitter user categories play a leading role on social media because they influence each other's agenda. It is possible that WHO and different categories of Twitter users pay attention to each other's agenda and interact with each other on some topics related to COVID-19 in a bidirectional way (or multidirectional way).

Vargo and Guo (2017) also suggested that different news media pay attention to and are impacted by each other's agenda. Therefore, agenda setting is not always a 1-way communication mechanism from the mainstream media to the public. Actually, by making large-scale communication possible through social media, agenda setting is no longer only in the control of certain types of users (Boynton & Richardson Jr, 2016). An agenda can be created by laypeople on social media and shape the media agenda or vice versa (Neuman et al., 2014).

Two Levels of the Agenda-Setting Effect on Twitter

A limitation in most network agenda-setting studies is that it is not clear if the public agenda is directly impacted by gatekeepers (e.g., news media) or if other sources are involved too in influencing public agenda. For instance, the study by Vu et al. (2014) compared the most prominent issues in the national news media in the United States from 2007 to 2011 (extracted from the Pew Research Center's PEJ) with public opinion extracted from the Gallup Poll results (which has been surveying the public since 1939 about the most important problems facing the United States). In such studies, it is hard to determine if the national news media impact public agenda or whether other sources are also involved. One way to minimize this methodological limitation is to analyze the opinions of the users who follow a gatekeeper's account on social media or to analyze those users subscribed to a news media channel, such as CNN.

To fill this gap, this study investigated 6 Twitter user categories that follow the WHO's Twitter account. From the results of this study, it can be concluded that there are 2 levels of the agenda-setting effect on Twitter—one at the aggregate level (see Guo, 2017), that is all social media users (e.g., WHO followers on Twitter), and another at the Twitter user category level, in which each user category would be influenced differently by the agenda that is set by a gatekeeper. It may also be the case that the interaction among the agenda networks of all Twitter user categories builds the overall Twitter agenda network.

Practical Implications for WHO

The results of this study can inform policy and be used to prepare for future pandemics in several ways: First, WHO should define a clear strategy as how to use social media during pandemics to convey its messages to the public. WHO should have a plan for what topics are more critical for the public during similar public health emergencies and work on transferring them to the public agenda.

Second, how health messages are framed and presented to the public is important. WHO can identify the needs of social media users and provide information-related benefits to them by framing and presenting more effective messages during public health emergencies. The strategic framing of public health messages can help WHO to have greater impact on social media users. For instance, to design more effective messages and attract more audiences, WHO can frame its messages by using hashtags that are popular and engaging among the public, or are more likely to be adopted by them (Tahamtan et al., 2021).

Third, using hashtags can lead to establishing and promoting important public health, social, political, or environmental agendas (Hemsley, 2019). Hashtags have various functions, such as information searching and discovering, information organization, information distribution, information collection, and protecting information (Potnis & Tahamtan, 2021). Our analysis of WHO tweets indicated that

WHO had used only a few hashtags related to COVID-19 in its tweets, including #safehand, #togetherathome, #handhygiene, #unitedagainstcoronavirus, and #stayhome. WHO can use more hashtags during public health emergencies to convey its messages to people and create more engagement with them (Tahamtan et al., 2021). For instance, WHO could frame its message about “credibility” of information, using a hashtag like “#WHOFactChecker, as follows: “#WHOFactChecker recommends that you continue to take appropriate actions to protect yourself and those around you in the summer as there is no evidence that warm weather can kill the #COVID-19 virus.”

Fourth, this study suggests that there could be a “two-way” or “multiway” agenda-setting effect on social media, where WHO, CDC, the US government, and politicians interact with and influence each other’s agenda. Therefore, in future public health emergencies, WHO can determine which topics should be promoted on social media during different phases of a pandemic and collaborate with other gatekeepers such as CDC to collectively make them salient in the public.

Study Limitations

This study investigated only 6 Twitter user categories. There are other types of users following WHO on Twitter, which can be studied in future work, such as artists and athletes. Another limitation of using Twitter data is that Twitter users are not representative of the entire population, because not all individuals use Twitter.

The agenda of WHO followers about COVID-19 could have been influenced by other resources too, such as the CDC or any other government agency. Future studies should find ways to take the effect of sources other than WHO into consideration. Surveys and interviews can provide more insights into the impact of WHO on the opinion of its followers on Twitter regarding COVID-19.

The 7 topics promoted by WHO on Twitter could possibly also be found in the messages shared on Twitter by other resources such as the US government. It could be the case that the 6 categories of WHO followers on Twitter were also propagating the agenda by other resources and not specifically that of WHO. Therefore, although this study suggests that there can be a “two-way” agenda-setting effect on social media, there could also be a “multiway” agenda-setting effect where various sources of information impact each other’s agenda.

This study was limited to tweets written in English. Analyzing tweets in other languages may provide new insights on the agenda-setting effect of WHO on Twitter.

Although this study analyzed a sample of tweets in the first 6 months in 2020, it is possible that the analysis of all the tweets posted by WHO and its followers in the second half of 2020 could lead to different findings.

Another limitation in this study is that, although we attempted to make the Twitter user categories as exclusive as possible; there might be some overlap among different categories. For instance, a Twitter user account could fall into the academics and print and electronic media categories.

CONCLUSIONS

This is among the first studies that demonstrate the presence of network agenda-setting effects between WHO and its followers on Twitter. In line with the network agenda-setting model, this study showed that the issues promoted by WHO about COVID-19, such as “credibility” or “surveillance,” were linked together in a network.

This study extends theorizing on agenda setting by providing evidence that agenda-setting effects vary by Twitter user categories and issues. For instance, WHO only influenced “surveillance” in politics and print and electronic media, or health care professionals only influenced “charity” in WHO, while WHO and legal professionals did influence each other.

This study also extends theorizing on agenda setting by indicating that, while network agenda setting is known as a “1-way” model, there can be “two-way” or “multiway” effects of agenda setting on social media, where WHO, its followers on Twitter such as politicians and healthcare professionals, and possibly other groups and organizations impact each other’s agenda.

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CHAPTER 4: KEY CONCLUSIONS AND FUTURE WORK

Concluding Remarks Related to Chapter 2

Chapter 2 of the dissertation explored how the public framed their opinion about the COVID-19 crisis on Twitter, using hashtags, in the March of 2020, when WHO declared it as a global pandemic and most countries worldwide instituted a full or partial lockdown. This study collected and analyzed 22 trending hashtags in the US in March 2020 and other hashtags associated with them, along with 694,582 tweets containing those hashtags to identify how people framed their opinion about the pandemic. The framing theory was used as a framework, which states the way messages are framed and presented, lead to varied influences on public opinion (Chong & Druckman, 2007). Thematic analysis was applied to the hashtags and tweets to identify the frames in public opinion.

The results revealed 9 frames about the pandemic in public opinion on Twitter and investigated what frames received greater public attention. This study contributes to the framing theory and research by indicating that trending hashtags are appropriate tools for framing analysis of social media data. It also proposes a novel approach to measure public attention on social media, where the score of public engagement with frames and public adoption of frames were measured. Public engagement was measured by the number of likes and retweets each frame had received. Public adoption was measured by the number of unique user accounts in each frame.

This study also suggests practical implications that frames like “solidarity” and hashtags like “#StayStrong” can be used beyond the COVID-19 pandemic in any crisis to design effective messages to impact public opinion in a positive way.

Future Work

Chapter 2 answered important questions about how people framed their opinion about the COVID-19 pandemic on Twitter, but also raises questions to investigate in future research.

This research found 9 frames, which can further be explored in future public health crises and expanded in other contexts. For instance, it is worth studying which frame can be applied to other future crises such as earthquakes or tornados. It also provides useful orientation for future empirical and theoretical research that aims to investigate the frames on social media during global (health) crises.

This study did not investigate how different groups of people like citizens, officials, researchers, journalists, and organizations, framed COVID-19 differently, which is worth studying in future studies.

Furthermore, experiments should be designed to manipulate the type and category of frames (while keeping other variables constant) to understand to what degree hashtags affect public collective attention (see Shteynberg, 2015) on social media.

Future research can also investigate how frames and hashtags emerge, evolve, and operate and how they succeed in achieving sustainability during different phases of a crisis, such as precrisis, the initial event, maintenance, resolution, and evolution (Reynolds & W. Seeger, 2005).

Additionally, another concept that can be examined in future research is public compliance to health messages and guidelines. Public compliance to COVID-19 can be evaluated by different measures such as “compliance to public health and social measures in preventing the spread of COVID-19” (Padidar et al., 2021, p. 4). Future research should also investigate how health messages should be designed and framed to increase public compliance to health guidelines during pandemics.

Concluding Remarks Related to chapter 3

Chapter 3 utilized the agenda-setting theory, particularly the network agenda-setting model, content analysis, text mining, network analysis, and several statistical tests to investigate the network agenda-setting effect of the WHO's Twitter account on its followers on Twitter in the first half of 2020. It collected 7,090 tweets posted by WHO, among which only 4,979 tweets were related to COVID-19. The content analysis of the WHO tweets revealed 7 issues related to the pandemic, including "prevention," "solidarity," "charity," "teamwork," "ill-effect," "surveillance," and "credibility." These issues constituted the WHO agenda about COVID-19 from January 01 to July 31 in 2020.

It was also investigated if the WHO agenda about COVID-19 was correlated with the agenda of the 6 Twitter user categories that follow WHO on Twitter. The results indicated the correlation was positive and significant for all Twitter user categories, proving that the agenda network of the WHO impacts the agenda network of its followers on Twitter. Additionally, the Granger causality test was used to investigate if the issues promoted by the WHO impacted the corresponding issues in the 6 Twitter user categories and vice versa.

The results indicated that both the WHO and Twitter user categories influenced each other on certain issues. For instance, WHO only influenced "surveillance" and "ill-effect" in the print and electronic media and print and electronic media influenced "surveillance" and "prevention" in WHO. It can be concluded that WHO and its followers on Twitter impact certain issues in each other's agenda during public health emergencies. Based on these results, it can be concluded there is a "two-way" or even "multiway" agenda-setting effect between WHO and its followers on Twitter, where they can influence the agenda of each other.

Future Work

Future studies can determine which social media user categories and top influencers within them, WHO should reach out to, if it wants to have more impact on social media users.

Future studies in this area can also study whether and to what extent WHO has made strategic use of hashtags to communicate its messages about COVID-19 to the public. Additionally, the role of hashtags used by WHO can be studied in setting its COVID-10 agenda and its effect on public opinion.

Although using social media data provides a legitimate method for studying the agenda-setting effect of the WHO, more empirical research, including surveys and interviews, are needed to understand the role of WHO in shaping public agenda on social media.

This study did not investigate whether the 6 Twitter user categories impacted each other's agenda about the COVID-19 pandemic. Such impacts can be examined by exploring, for instance, the network agenda-setting effect between academics and health care professionals on Twitter.

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APPENDIX

Table 17. The keywords used to classify WHO followers to 6 Twitter user categories.

Twitter user categories	Keywords used to analyze the descriptions used in the Twitter users accounts
Academics (except healthcare professional s)	lecturer, professor, PhD, student, Ph.D., postdoc, postdoctoral, doctoral, msc, master, MS, BS, bachelor, undergrad, grad, graduate, undergraduate, scientist, postgrad, faculty, chancellor, university, college, provost, vice-provost
Politicians	campaign, campaigner, republican, democrat, senator, mayor, governor, minister, ministry, counselor, parliament, politician, representative, statesman, stateswoman, congressman, congresswoman, spokesman, spokeswoman, senate, chairwoman, chairman, representing, congressional, commissioner, ambassador, congress, councilmember, assembly member, assemblywoman, assemblyman, assembly, councilman, councilwoman congressional, Whitehouse

Table 17 continued.

Twitter user categories	Keywords used to analyze the descriptions used in the Twitter users accounts
Print and Electronic Media	writer, author, journalist, logger, columnist, communicator, reporter, producer, storyteller, podcaster, youtuber, news, newsman, newswoman, pressman, presswoman, journal, publish, publisher, publishing, peer-reviewed, reviewed, press, elsevier, wiley, emerald, wolters, reutckwell, mdpi, palgrave, routledge, springer, sage, clarivate, bmc, bmj, plos, iee, cnn, fox, msnbc, bbc, cbs, nbc, abc, wion, cnbc, broadcasterbcgtn, jazeer
Healthcare professionals	physician, doctor, nurse, midwife, dentist, pharmacist, microbiologist, virologist, oncologist, hematologist, epidemiologist, physiologist, pathologist, endocrinologist, nephrologist, neurologist, geneticist, geriatrician, surgeon, optometrist, ophthalmologist, therapist, podiatrist, chiropract, pedorthist, pediatrician, immunologist, anesthesiologist, cardiologist, dermatologist, endocrinologist, gastroenterologist, hematologist, obstetrician, gynecologists, osteopath, otolaryngologist, physiatrist, podiatrist, psychiatrist, pulmonologist, radiologist,

Table 17 continued.

Twitter user categories	Keywords used to analyze the descriptions used in the Twitter users accounts
Healthcare professionals	rheumatologist, urologist, infectious disease, physician, 'infectious disease specialist, 'Johnson & Johnson', renvartis, merck, glaxosmithksanofi, abbvie, takeda, beristol-myers, pharmaceutca, amgen, gilead, biogen, moderna, sinovac, novavax, cfra, allergan, abbott, stryker, regeneron
Legal professionals	lawyer, attorney, court, justice, lawmaker, judge, solicitor, barrister, jurist, jury, paralegal, courtroom, arbitrator, legislator
Private sector (except drug and pharma companies)	corporation, Inc., ceo, corporate, company, enterprise, cfo, cio, coo, cmo, cfo, cto, cco, firm

Table 18. List of issues identified by content analysis and their corresponding keywords and hashtags.

Issues	Keywords and hashtags
Teamwork	Contributing, coordinate, accountability, cooperation, contributions, collaboration, collective, commitment, commitments, coordinating, contribution, leadership, preparedness, resolution
Charity	donation, pledged, donations, fundraisers, pledges, financial, fund, donate, donated, pledge, fundraiser, donating, funders, funding, pledging
Surveillance	tracing, investigation, trace, monitor, monitoring, screening, surveillance

Table 18 continued.

Issues	Keywords and hashtags
Prevention	cleanser, handrub, clean, cover, cleaning, disinfect, handwashing, preventive, precautions, mask, masks, handwash, hygiene, preventing, wash, prevent, washing, preventable, prevention, sanitation, wear, covering, #safehands, #handhygiene, handwashing, vaccines, vaccine, vaccinated, vaccination, vaccinations, vaccinated, #vaccineswork, #vaccines, protect, protecting, protective, protects, lockdown, quarantine, lockdowns, isolate, isolation, isolated, #halthyatHome, #togetheratHome, #beactive, #stayhome, #stayathome, distance, distancing
Solidarity	#unitedagainstcoronavirus, #withrefugees, compassion, help, humanitarian, kindness, resilience, solidarity, unity
Ill-effect	disruptions, consequences, disrupted, disruption, depression, #endviolence, #mentalhealth, #stopelderabuse, abuse, threatens, violence
Credibility	facts, rumors, misinformation, fact, #knowthefact, #knowthefacts, #takecarebeforeyoushare

A1. The keywords and hashtags used to find the WHO tweets relevant to COVID-19

#stayhome, distancing, lockdown, quarantine, isolate, china, wuhan, handwashing, #handwashing, #handhygiene, #safehands, #2019ncov, outbreak, pandemic, masks, vaccines, #vaccines, #coronavirusDrTedros, #UnitedAgainstCoronavirus, #knowTheFact, #KnowTheFacts, #HandHygiene, #COVID19DrTedros, #togetherathome, #covid—19, #coronalockdown, #covidlockdown, #covid19lockdown, #covidquarantine, #coronaquarantine, #coronavirusquarantine, #pandemic, pandemic, #covid-19, #covid19, covid19, #covid, covid, #corona, corona, #coronavirus, coronavirus, #wuhanvirus, #2019novelcoronavirus, #chinacoronavirus, #coronaoutbreak, #coronaphobia, #coronavirusoutbreak, #novelcoronaviruspneumonia, #wuhanconoravirus, #wuhanpneumonia, #coronaviruspandemic, #coronapandemic, #coronacrisis, #coronaviruscrisis, covid2020, #kungflu, #covidpandmeic, #coronapademic, #coronavirusvaccine, #coronavirusvaccines, #coronavirusupdates, #coronaupdates, #covidvaccine, #coronaepidemic, #coronavaccination, #coronavaccine, #postcovid, #covidinfection, #covidisease, #2019_ncov, #coviddebts, #covidrehab, #SARSCoV2, #covidpositive, #covidrecovery, #covid19Walkout, #coronavirus19, #covidplague, #coronaplague, #covidpandemic, #covidinformation, #covid19plague, #covid19pandemic, #covid19research, #covidresearch, #coronaresearch, #highriskcovid19, #covidhasnoborders, #COVID—19, #covid-safe, #covidheros

A2. The keywords and hashtags used to find tweets relevant to COVID-19 in the 6 Twitter user categories

#covid—19, #coronalockdown, #covidlockdown, #covid19lockdown, #covidquarantine, #coronaquarantine, #coronavirusquarantine, #pandemic, pandemic, #covid-19, #covid19, covid19, #covid, covid, #corona, corona, #coronavirus, coronavirus, #wuhanvirus, #2019novelcoronavirus, #chinacoronavirus, #coronaoutbreak, #coronaphobia, #coronavirusoutbreak, #novelcoronaviruspneumonia, #wuhanconoravirus, #wuhanpneumonia, #coronaviruspandemic, #coronapandemic, #coronacrisis, #coronaviruscrisis, covid2020, #kungflu, #covidpandmeic, #coronapademic, #coronavirusvaccine, #coronavirusvaccines, #coronavirusupdates, #coronaupdates, #covidvaccine, #coronaepidemic, #coronavaccination, #coronavaccine, #postcovid, #covidinfection, #coviddisease, #2019_ncov, #coviddebts, #covidrehab, #SARSCoV2, #covidpositive, #covidrecovery, #covid19Walkout, #coronavirus19, #covidplague, #coronaplague, #covidpandemic, #covidinformation, #covid19plague, #covid19pandemic, #covid19research, #covidresearch, #coronaresearch, #highriskcovid19, #covidhasnoborders, #COVID—19, #covid-safe, #covidheros.

Table 19. The matrix of agenda network for private sector on Twitter.

	T	Ch	Su	P	So	Ill	Cr
T	1985	131	27	300	239	27	17
Ch	131	2537	13	443	563	25	2
Su	27	13	1064	234	158	6	3
P	300	443	234	12093	1234	170	115
So	239	563	158	1234	5938	150	49
Ill	27	25	6	170	150	1061	4
Cr	17	2	3	115	49	4	623

T = Teamwork, Ch= Charity, Su = Surveillance, P = Prevention, So = Solidarity, Ill-effect
= Ill, Cr = Credibility

Table 20. The matrix of agenda network for electronic and print media on Twitter.

	T	Ch	Su	P	So	Ill	Cr
T	3547	233	49	510	396	40	58
Ch	233	4926	30	857	996	69	25
Su	49	30	2269	510	136	15	24
P	510	857	510	35159	2476	526	391
So	396	996	136	2476	11634	265	159
Ill	40	69	15	526	265	2509	21
Cr	58	25	24	391	159	21	2303

T = Teamwork, Ch= Charity, Su = Surveillance, P = Prevention, So = Solidarity, Ill-effect = Ill, Cr = Credibility.

Table 21. The matrix of agenda network for legal professionals on Twitter.

	T	Ch	Su	P	So	Ill	Cr
T	1428	99	20	220	146	33	17
Ch	99	1760	11	285	390	34	9
Su	20	11	691	167	37	7	7
P	220	285	167	9639	771	245	132
So	146	390	37	771	3872	120	50
Ill	33	34	7	245	120	1138	7
Cr	17	9	7	132	50	7	667

T = Teamwork, Ch= Charity, Su = Surveillance, P = Prevention, So = Solidarity, Ill-effect = Ill, Cr = Credibility.

Table 22. The matrix of agenda network for healthcare professionals on Twitter.

	T	Ch	Su	P	So	Ill	Cr
T	5089	226	100	724	533	64	36
Ch	226	4780	28	868	918	63	18
Su	100	28	3787	943	238	27	30
P	724	868	943	43233	3657	574	688
So	533	918	238	3657	16585	319	163
Ill	64	63	27	574	319	3028	14
Cr	36	18	30	688	163	14	2807

T = Teamwork, Ch= Charity, Su = Surveillance, P = Prevention, So = Solidarity, Ill-effect = Ill, Cr = Credibility.

Table 23. The matrix of agenda network for academics on Twitter.

	T	Ch	Su	P	So	Ill	Cr
T	7302	443	114	1015	759	96	70
Ch	443	7908	53	1372	1625	123	29
Su	114	53	4162	939	275	31	19
P	1015	1372	939	52091	4401	841	782
So	759	1625	275	4401	21383	514	227
Ill	96	123	31	841	514	4695	36
Cr	70	29	19	782	227	36	3370

T = Teamwork, Ch= Charity, Su = Surveillance, P = Prevention, So = Solidarity, Ill-effect = Ill, Cr = Credibility.

Table 24. The matrix of agenda network for politicians on Twitter.

	T	Ch	Su	P	So	Ill	Cr
T	2998	218	39	445	455	62	17
Ch	218	2667	14	543	589	35	10
Su	39	14	867	233	64	5	3
P	445	543	233	12735	1305	283	140
So	455	589	64	1305	6147	157	70
Ill	62	35	5	283	157	1221	3
Cr	17	10	3	140	70	3	734

T = Teamwork, Ch= Charity, Su = Surveillance, P = Prevention, So = Solidarity, Ill-effect = Ill, Cr = Credibility.

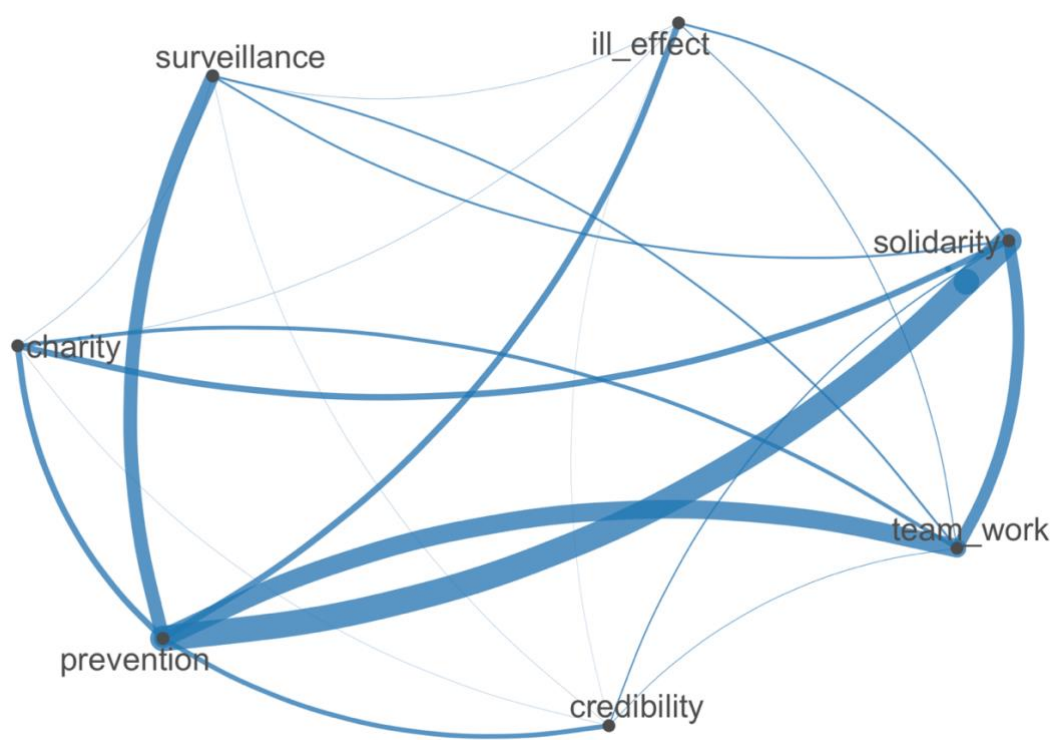


Figure 6. The agenda network of WHO.

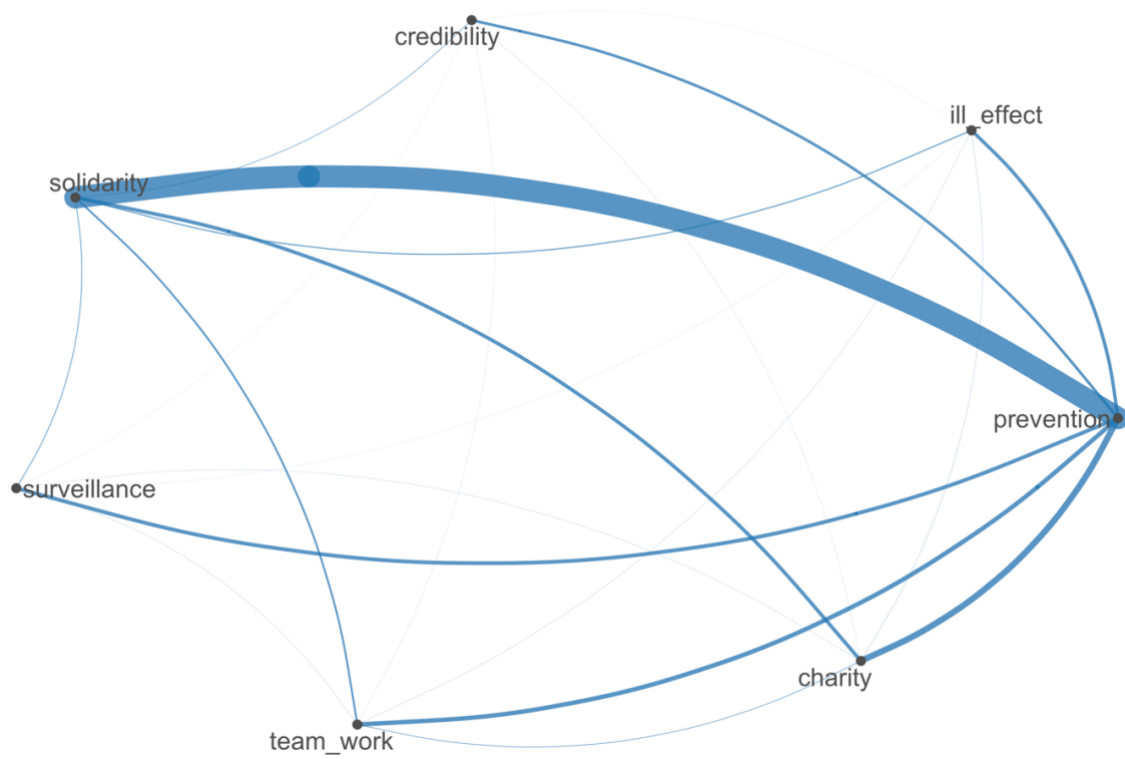


Figure 7. The agenda network of WHO followers (6 Twitter user categories together).

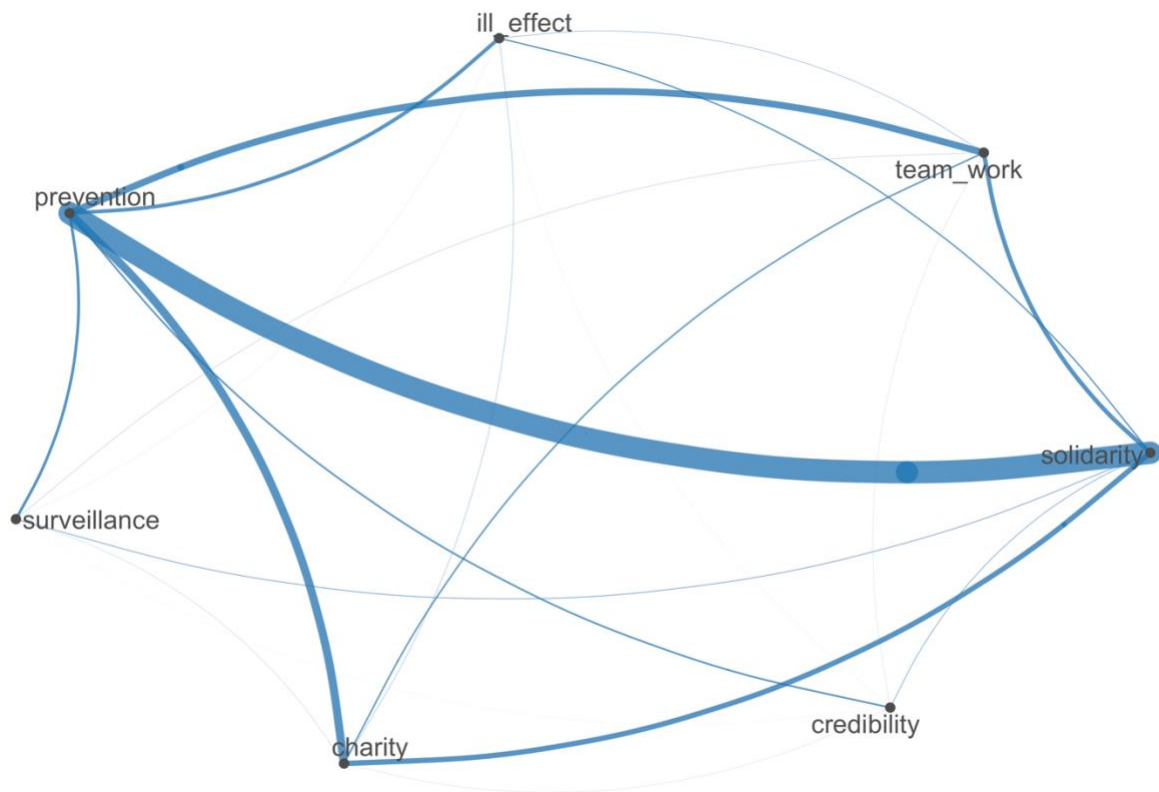
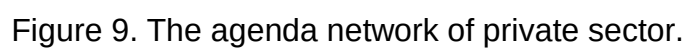


Figure 8. The agenda network of politicians.



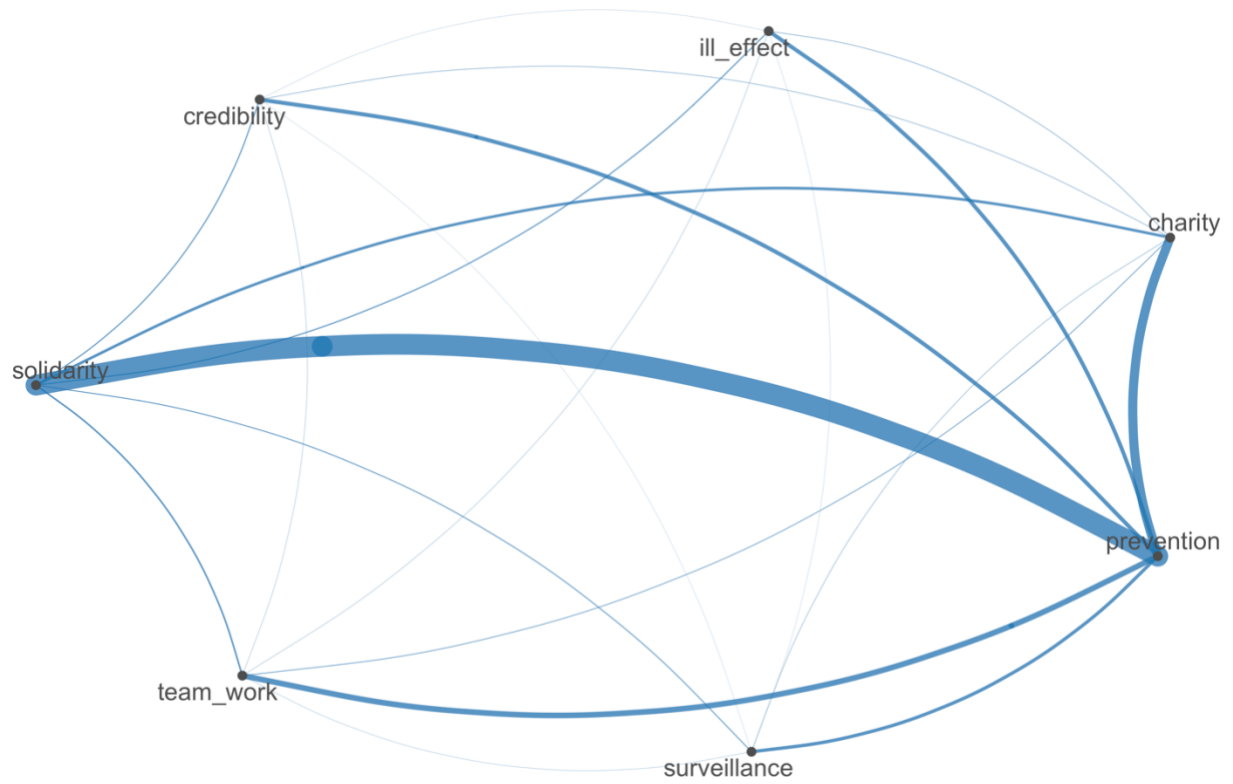


Figure 10. The agenda network of print and electronic media.

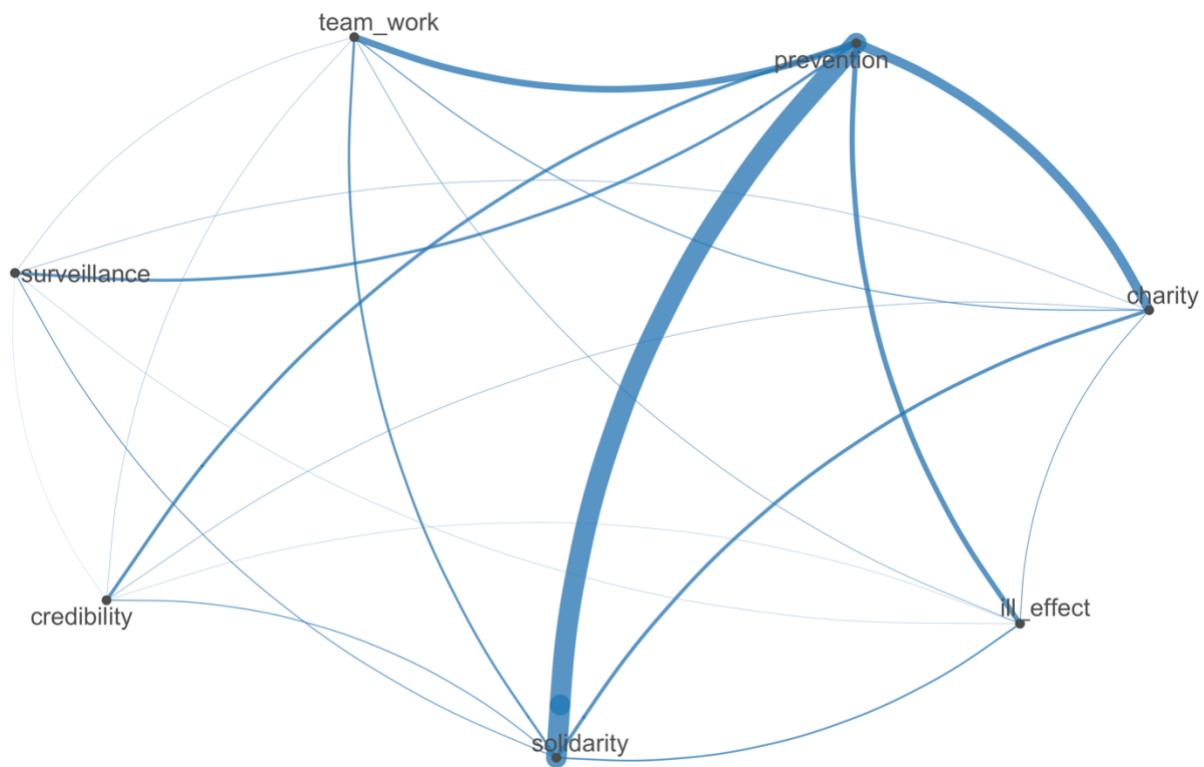


Figure 11. The agenda network of legal professionals.

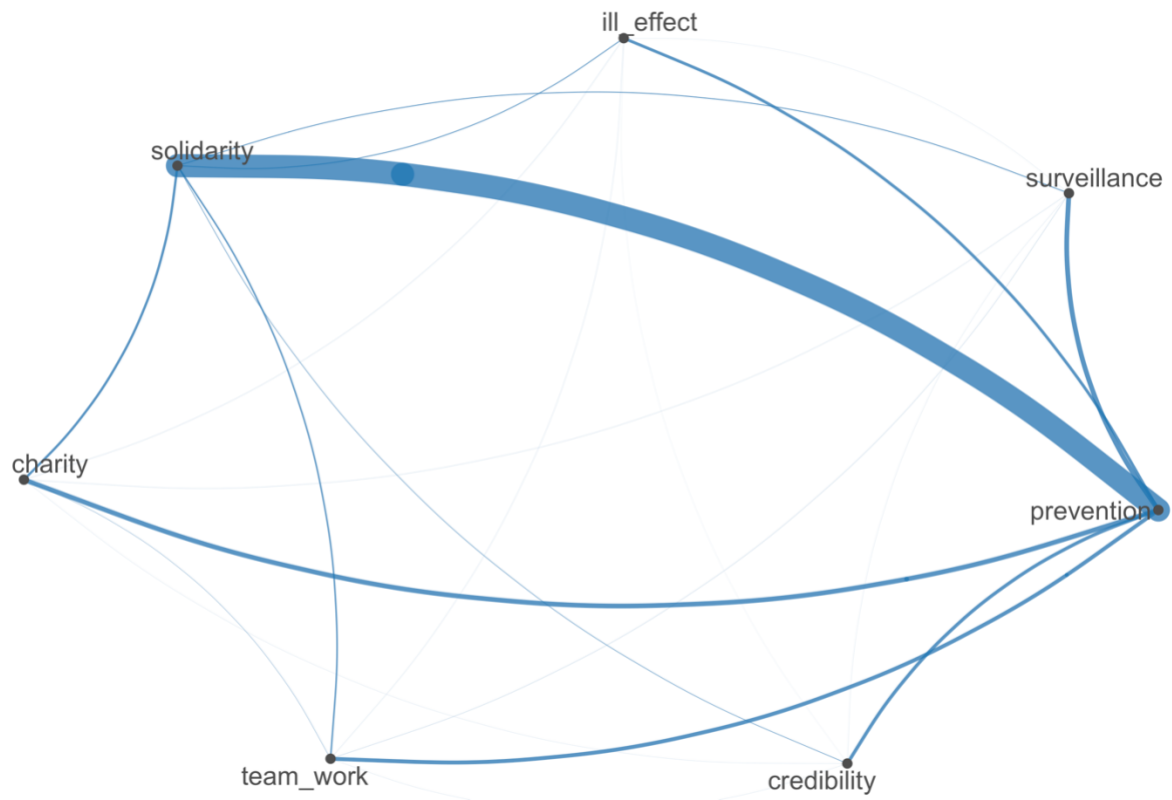


Figure 12. The agenda network of healthcare professionals.

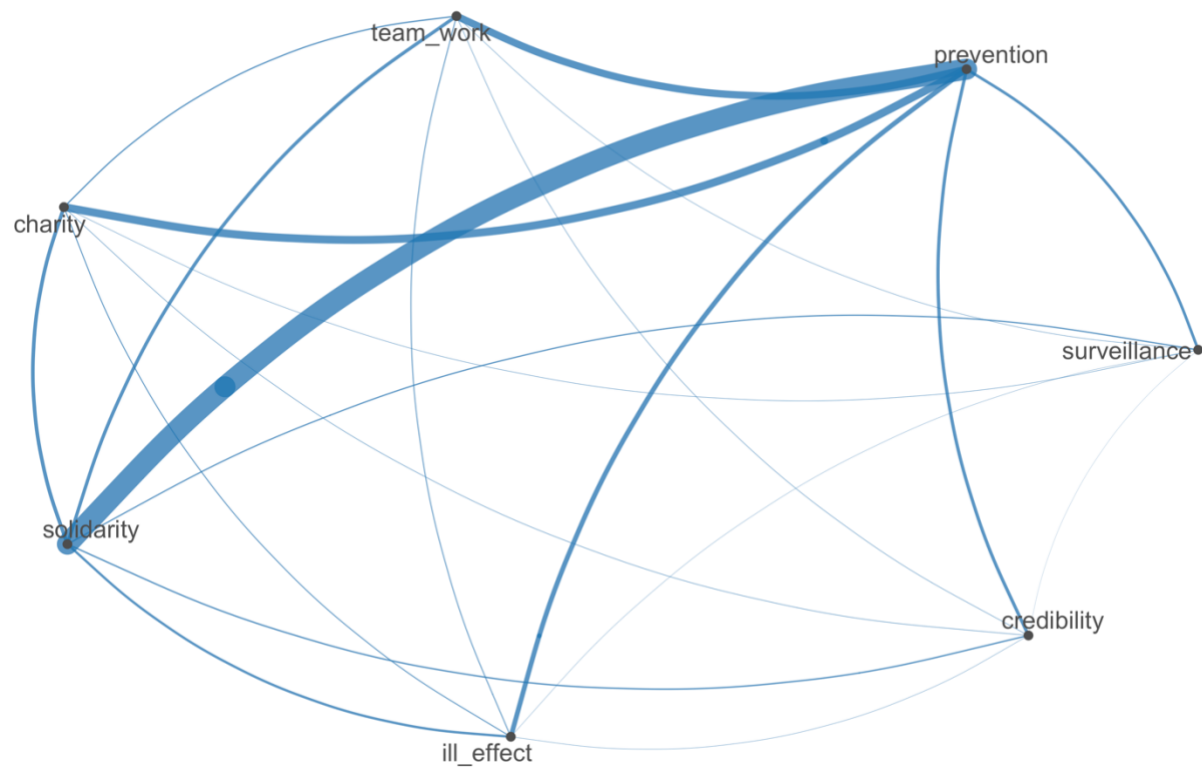


Figure 13. The agenda network of academics.

Granger causality tests results

Table 25. Granger test of causality of WHO on healthcare professionals and vice versa.

	Agendas	F-Test	P-value
WHO Granger causes Healthcare professionals	Teamwork	0.34	0.88
	Charity	0.39	0.86
	Surveillance	2.35	0.12
	Prevention	0.33	0.89
	Solidarity	0.50	0.77
	Ill-effect	0.81	0.58
	Credibility	0.61	0.70
Healthcare professionals Granger causes WHO	Teamwork	0.19	0.96
	Charity	37.93	0.001
	Surveillance	2.03	0.16
	Prevention	0.78	0.58
	Solidarity	0.99	0.47
	Ill-effect	0.85	0.55
	Credibility	0.60	0.71

Table 26. Granger test of causality of WHO on academics and vice versa.

	Agendas	F-Test	P-value
WHO Granger causes Academics	Teamwork	0.06	0.99
	Charity	0.32	0.91
	Surveillance	2.76	0.08
	Prevention	0.24	0.94
	Solidarity	0.30	0.90
	Ill-effect	0.49	0.78
	Credibility	12.15	0.001
Academics Granger causes WHO	Teamwork	0.62	0.69
	Charity	4.62	0.04
	Surveillance	3.17	0.06
	Prevention	3.07	0.06
	Solidarity	0.71	0.61
	Ill-effect	0.71	0.63
	Credibility	6.10	0.001

Table 27. Granger test of causality of WHO on legal professionals and vice versa.

	Agendas	F-Test	P-value
WHO Granger causes Legal professionals	Teamwork	0.15	0.98
	Charity	0.55	0.73
	Surveillance	3.25	0.05
	Prevention	0.39	0.84
	Solidarity	1.25	0.37
	Ill-effect	1.09	0.42*
	Credibility	0.71	0.64
Legal professionals Granger causes WHO	Teamwork	2.23	0.13
	Charity	2.50	0.10
	Surveillance	3.13	0.06
	Prevention	1.08	0.42
	Solidarity	1.76	0.23
	Ill-effect	0.52	0.76*
	Credibility	1.81	0.22

* BoxCox transformation was used for this variable

Table 28. Granger test of causality of WHO on politicians and vice versa.

	Agendas	F-Test	P-value
WHO Granger causes Politicians	Teamwork	0.19	0.96
	Charity	0.41	0.83
	Surveillance	5.13	0.03
	Prevention	0.41	0.83
	Solidarity	0.27	0.92
	Ill-effect	0.86	0.54
	Credibility	2.80	0.09
Politicians Granger causes WHO	Teamwork	1.09	0.42
	Charity	0.63	0.68
	Surveillance	0.60	0.72
	Prevention	13.21	0.001
	Solidarity	0.32	0.89
	Ill-effect	1.64	0.24
	Credibility	8.06	0.001

Table 29. Granger test of causality of WHO on private sector and vice versa.

	Agendas	F-Test	P-value
WHO Granger causes Private sector	Teamwork	1.99	0.16
	Charity	0.04	0.99
	Surveillance	2.59	0.094*
	Prevention	0.17	0.97
	Solidarity	1.07	0.41
	Ill-effect	1.37	0.31
	Credibility	7.12	0.001
Private sector Granger causes WHO	Teamwork	1.07	0.39
	Charity	2.11	0.15
	Surveillance	1.48	0.28*
	Prevention	1.05	0.45
	Solidarity	2.25	0.12
	Ill-effect	7.35	0.001
	Credibility	4.33	0.02

* BoxCox transformation was used for this variable

Table 30. Granger test of causality of WHO on print and electronic media and vice versa.

	Agendas	F-Test	P-value
WHO Granger causes Media	Teamwork	0.06	0.99
	Charity	0.32	0.90
	Surveillance	9.33	0.001
	Prevention	0.21	0.94
	Solidarity	0.37	0.86
	Ill-effect	4.02	0.02
	Credibility	0.52	0.72
Media Granger causes WHO	Teamwork	0.57	0.71
	Charity	4.25	.051
	Surveillance	3.7	0.04
	Prevention	15.04	0.001
	Solidarity	0.49	0.78
	Ill-effect	0.52	0.72
	Credibility	2.5	0.1

VITA

Iman Tahamtan earned his undergraduate and master's degrees in Medical Information Sciences (MLIS) in Iran. His master's thesis investigated how mobile devices were adopted and used by doctors to access health information in medical settings. He worked as a faculty member at Hormozgan University of Medical Sciences in Iran from December 2012 to December 2015. In this role, he received the Faculty Excellence in Research award in 2014 and 2015 and the Outstanding Supervisor award in 2015.

Iman joined the University of Tennessee in Knoxville (UTK) in August 2016, where he earned his Ph.D. in Communication and Information, Information Sciences Concentration, in 2021. Iman is the first doctoral student at the College of Communication and Information (CCI) at UTK who wrote a manuscript style dissertation. His first manuscript identified how the public framed its opinion about the COVID-19 pandemic on Twitter, and the second manuscript investigated the network agenda-setting effect of WHO on its followers on Twitter regarding the COVID-19 pandemic.

He taught several courses at CCI, including INSC-311 User-Centered Design, INSC-102 Technologies for Information Retrieval, INSC-210 Foundations of Information Technology, and INSC-102 Introduction to Computers. He also worked as a Scholarly Communication Research Assistant at the Scholars' Collaborative at the University of Tennessee Libraries for one year in 2019-2020.

Iman received several awards during his doctoral studies, such as the Graduate Student Research Award at CCI in 2018 and 2021, the Edward J. Meeman Fellowship for Successful Academic Performance at CCI in 2020 and 2021, and the 2019 New Leaders Award in the Association for Information Science and Technology (ASIS&T).

After his graduation, he started working as a Lecturer at the School of Information Sciences at UTK and a full-time Senior User Experience Researcher at the Machine Learning and Artificial Intelligence group at JP Morgan Chase in Columbus, Ohio.