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Global health, global networks: a multilingual network approach to COVID-19 tweets in Norway, Korea, and Italy

Jessica Yarin Robinson [1]

[1]Department of Media & Communication, University of Oslo

Abstract:
Social media have created new opportunities for public health communicators to reach citizens without the filter of the news media. But these platforms also pose the challenge of having to compete with a wider variety of other actors – actors who, in a global pandemic, may be inside or outside the country. This transnational dimension of health communication, while alluded to in the academic literature, is still little understood, raising the need for new methodologies. Using large Twitter datasets from the period of the first pandemic lockdown in Norway, Italy, and South Korea, this paper demonstrates the use of multilingual network data for understanding health communication. The findings suggest that such a methodological approach, which reveals users' transnational networks, can help identify the larger networks in which users interact and find health information, including global sources of misinformation.

Keywords: COVID-19, Language, Global Communication, Network Analysis, Twitter, Misinformation

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Corresponding author:
Jessica Yarin Robinson
Department of Media & Communication
University of Oslo, Oslo, Norway
E-mail: j.y.robinson@media.uio.no

Introduction

Twitter has become one of the critical sites for public health communication, and one of the most studied platforms in health communication research (Choi & McKeever, 2020; Guidry, et al., 2020; Mitchell & Beanlands, 2022; Park et al., 2016; Park et al., 2022). The open network structures and rapidity of Twitter make the platform highly responsive to health crisis (Hagen et al., 2018). Yet these structures also create opportunities for new voices not traditionally part of national health communication models (Hellsten et al., 2019; Kamiński et al., 2021; Park et al., 2022). Among these new voices are those from abroad, made more readily available through global interaction (Choi et al., 2021; Househ, 2016). This raises the need for Twitter research that moves beyond national-level conceptions of public information seeking and reflects the increasingly global nature of public health (Guidry et al., 2020; Sachs et al., 2022).

Yet while there are greater efforts at comparative research (Choi et al., 2022; Guidry et al., 2020; Tagliacozzo et al., 2021), so far limited research has been devoted to understanding the transnational flows of health information online. This is important because these broader networks may reflect a key development in response to global risk (Beck, 2011), while also potentially threatening the efficacy of locally relevant messages, due to differences in cultural contexts (Choi & McKeever, 2020; Guidry et al., 2020). Moreover, Twitter is one of the platforms driving the circulation of misinformation and conspiracy theories about health topics (Mitchell & Beanlands, 2022; Rosenberg et al. 2020; Vijaykumar et al., 2018; Yang et al., 2021). The formation of oppositional networks around health issues has been identified as a major threat to future pandemic control, and expert panels have suggested that identifying sources of misinformation is a key priority (Sachs et al., 2022). Thus, for health communication researchers and practitioners, understanding the public's global context can aid strategies to ensure quality health information. Househ (2016) argues "there is a need to develop more tools to be used by researchers, healthcare organizations, and policy makers" that can shed light on the global scope of the networks in which users find, share, and discuss health information (p. 476).

This paper responds to this call through an investigation of information-seeking behaviors about Covid-19 in Twitter networks in Norway, Italy, and South Korea. These countries represent diverse political, media, and pandemic environments (Hallin & Mancini, 2004; Newman et al., 2021), providing insight into different health communication contexts and their relationship with global sources of information. Using global datasets from the height of the Covid-19 pandemic, the paper demonstrates the use of multilingual network analysis for uncovering global network structures and major information hubs outside the national sphere. This approach moves away from previous approaches to global health communication research that may overstate the role of American sources (Househ, 2016; Mittelmeier & Cockayne, 2022; Yang et al., 2021).

The results show that users' global networks do not adhere to the same structures as networks in the national languages; in the case of Norway and Italy, globally oriented networks tended toward greater clique-like structures that reveal strong transnational connections in oppositional, "Covid-skeptic" subnetworks. The paper argues that the multilingual network analysis illuminates the broader environment in which citizens find information about disease. In this way, the paper contributes, first, to the literature on the use of social media during the Covid pandemic in these countries, and second, to the methodological toolbox for researchers studying this and future public health events. The paper ends with a discussion of the implications for public health communication and suggests future lines of investigation.

Literature Review

Health communication and social media

Social media have become increasingly popular tools for health organizations, scientific institutions, and government health agencies to transmit messages to the public. Literature on health communications indicates that digital platforms can serve a variety of purposes, including publicizing critical information during a crisis (Getchell & Sellnow, 2016), encouraging healthy behaviors (Park et al., 2016), and building relationships with members of the public (Guidry et al, 2017). Likewise, the literature also finds that citizens are increasingly turning to these platforms for health information (Chen & Wang, 2021; Choi et al., 2021), including in times of crisis (Hellsten et al., 2018; Hagen et al., 2018).

Despite the low cost of communication and potentially huge reach, research finds that health communicators often have trouble adapting to the new digital situation. Digital platforms create competition from a wide array of sources that people can seek health information from (Choi et al., 2021; 2013; Larson, 2020). These include traditional news media (Hagen, et al., 2018, p. 532; Vijaykumar et al., 2018), but studies increasingly find that social media also open spaces for other types of actors, including celebrities, self-appointed experts, and individual citizens (Acar & Muraki, 2011; Hellsten et al., 2018; Kamiński et al., 2021; Park et al., 2022) – a shift that Mancini (2020) has described as "deinstitutionalization" (p. 5767). One of the hazards of this shift is that individual actors may have contradictory messages to public health officials and scientific experts (Acar & Muraki, 2011; Choi et al., 2021; Okocha & Akpe, 2022). In a study on Zika virus information on Twitter, Vijaykumar et al. (2018) found that individual or "grassroots" users helped spread conspiracy theories, contributing to an environment where "science has become just another voice in the room" (Larson, 2020, p. xli).

Concerns about misinformation have gained an even greater sense of urgency in the wake of the Covid-19 pandemic that began in 2020. A report by the *Lancet*'s Covid-19 Commission argues that misinformation on social media bolstered opposition to routine public health measures (Sachs, 2022, p. 1225), and the commission recommends that social media platforms figure out how to regulate "anti-science messages" (p. 1249). Although

Twitter introduced content moderation measures in March 2020 (Twitter Inc., 2020), Rosenberg et al. (2020) suggest in the *Canadian Journal of Emergency Medicine* that Twitter was the prime culprit in creating hysteria, spreading falsities, and contributing to information overload around Covid-19. Media research has not confirmed that Twitter had the primary role, but scholars do find Twitter helped elevate claims about treatment with hydroxychloroquine (Blevins et al., 2021) and may have even contained proportionally more "low-credibility content" than Facebook (Yang et al., 2021, p. 13). Among the potential reasons for this attention on Twitter is its ability to respond quickly to live events and spread information quickly. In the following section, I will examine the way network structures influence the flow of information on Twitter.

Researching network structures and influence on Twitter

Twitter is a microblogging site with around 200 million daily active users worldwide (Twitter Inc., 2021, p. 43). Despite capturing a minority of the population in most countries (Newman et al., 2021), the microblogging site has become intertwined with many democratic media systems due to its heavy use by politicians, journalists, institutions, and celebrities. Twitter has been found to be particularly responsive to crisis and breaking news events, due to the ability to quickly send 240-character messages. Previous work has documented the use of Twitter for information dissemination during a number of health crises, including the H1N1 outbreak (Chew & Eysenbach, 2010); the Japanese tsunami (Acar & Muraki, 2011); the bird flu outbreak (Hellsten, et al., 2019); the Ebola outbreak (Guidry, et al., 2017; McInnes & Hornmoen, 2018); the Zika outbreak (Hagen et al., 2018; Vijaykumar, et al., 2018); and the West Virginia water contamination (Getchell & Sellnow, 2014).

Twitter users can interact with each other through several addressive functions (Papacharissi, 2015). These include @mentions, which identify and flag another user; @replies, respond directly to another user's tweet; and retweets, which "propagate the original tweet to a new set of audiences" (Bruns & Stieglitz, 2012, p. 161). Among the central features of Twitter is that users do not have to have previous relationships with each other to have these interactions. While research shows national and cultural borders still influence the flow of information on Twitter (Bruns et al., 2013; Froio & Ganesh, 2018; Leetaru et al, 2013; Takhteyev et al., 2012;), the addressive features have made the platform especially conducive to networks that cross geographic space (Ghemawat, 2016; Takhteyev et al., 2012).

Due to the vast variation in connections, information does not flow evenly across Twitter networks, even among users who are discussing the same topic. The way the network is structured – including the number of common ties between the members and how much they group into clique-like clusters – affects how information travels. Himelboim et al. (2017) developed a typology of Twitter networks based on these underlying structures, capturing their egalitarian, polarized, and fragmented natures. Moreover, Twitter communication generally follows a "rich get richer" pattern, or as Fuchs (2014) has called it, "asymmetrical visibility" (p. 192), in which a few users attract most of the attention. Health communication researchers have used principles from social network science to understand the flow of information across networks and identify "hubs" – highly visible users that act as important disseminators of information (Barabási, 2016; Getchell & Sellnow, 2016; Hagen et al., 2018; Hughes & Palen, 2009). For example, Yang et al. (2021) operationalized these principles to identify hubs of misinformation they call "infodemic superspreaders" (p. 9).

In addition to the virtual structures of Twitter networks, health communication researchers have become increasingly interested in the real-life geography underlying these networks. As Guidry et al. (2020) write, there is a need to understand the cross-border dimensions of public health information, "due to the public and scalable dimensions" of social media (p. 1137), as well as the increasing global nature of public health. Yet moving beyond national health and media systems creates challenges for researchers trying to study the flows of health information, as I discuss in the following section.

Researching global health communication on Twitter

One of the challenges of studying the geography of health communication on social media is that the very features that make communication so geographically dispersed also make it difficult to identify geography (Robinson, 2022). Researchers have used a variety of approaches to capture the global dimensions of health communication. One common practice to establish *a priori* a set of institutional actors of different national origins (e.g. Guidry et al., 2020; Choi & McKeever, 2020). Other studies have started with pieces of content known to be of particular national origins (Choi et al., 2021). These techniques provide a comparative perspective if not a view into the border-crossing nature of information, although this top-down approach runs the risk of failing to capture the deinstitutionalizing effects of social media, as described by Mancini (2022).

Other researchers have used a more bottom-up approach to investigate global health communication by capturing all tweets, regardless of source, referring to a particular topic. For example, Househ (2016) investigated global communication about Ebola on Twitter by identifying nearly 26 million tweets that include the term "ebola." Similarly, Yang et al.'s (2021) study on Covid-19 misinformation sharing identified tweets containing "coronavirus," "covid," and "sars" (see also Lwin et al., 2020; Mittelmeier & Cockayne, 2022).

Notably, in each of these cases, the researchers limit their corpus to English-language tweets. This choice can be justified in that English is the *lingua franca* of Twitter. That is, it is both the most common language on Twitter, and the most common second language among non-native speakers on Twitter (Mocanu et al., 2013). Even in countries with moderate or low proficiency in English, such as Chile and Turkey (Education First, 2019), one out of every 10 tweets is in English (Mocanu et al., 2013, p. 6). Thus, Mittelmeier and Cockayne (2022) argue using English tweets provides a snapshot of information sharing on "a global scale" (p. 3).

However, as Schünemann (2020) found in a study of tweets about climate change, using English as a stand-in for transnational communication may produce results dominated by users in the United States, and thus over-emphasizes American sources as major hubs of health information. Indeed, previous studies' findings are dominated by CNN, the *New York Times,* ABC News, and the *Washington Post,* and right-wing outlets like InfoWars and *The Gateway Pundit* (Househ, 2016, p. 474; Mittelmeier & Cockayne, 2022, p. 13; Yang et al., 2021, p. 7). Yet it is not clear how dominant these sources are in discussions outside of the United States.

In this paper, I propose an approach to researching global health communication that uses elements of the methods previously described. First, rather than identifying sources *a prior* and tracking their Twitter use (Guidry et al., 2020; Choi & McKeever, 2020; Choi et al., 2021), I employ *post factum* identification of users from a corpus of tweets. However, rather than relying on English-language tweets, I propose drawing on techniques used in the fields of political communication, social movements, and information science, yet so far little utilized in the area of health communication. This includes text-matching with locations provided in user profiles (see Hänska & Bauchowitz, (2019; Schünemann (2020), and identification of multiple language usage among users (Bruns et al., 2013; Chen et al., 2017; Hopke, 2015; Meraz & Papacharissi, 2013; Poell & Darmoni, 2012). In particular, I draw on the work of Eleta and Golbeck (2014), who use a multi-step method to study bilingual Twitter users. Unlike most of the geo-location and language-based approaches used previously (Hopke, 2015; Chen et al., 2017), this two-step method works on a user basis rather than a tweet basis. That is, after using language to identify users, it then retrieves previously unidentified tweets *from those same users* – accounting for the demonstrated multilingual practices of Twitter users. However, unlike Eleta and Golbeck (2014), who mapped single users' egocentric networks, in this paper I map the entire network of users discussing Covid.

This multilingual network method is applied to three case countries: Norway, South Korea, and Italy. The following question is posed: What can multilingual data reveal about global health communication? This is answered through three subquestions:

RQa: How do multilingual network structures differ from national language networks?

RQb*:* What information hubs are revealed by looking at multilingual data?

RQc: What are the global information hubs shared across all the case countries?

In the following section, I will outline the three countries used in this study.

Case countries

The SARS-CoV-2 virus was first identified in Wuhan Province, China, in late 2019. By March 2020, the World Health Organization declared Covid-19 a global pandemic, triggering closures of schools and businesses, and restrictions on travel across the world. Conservative estimates are that within five months 850,000 people had died from the virus (Sachs et al. 2020; 2022). The three case countries have been selected because they represent different types of media systems, political contexts, and Covid-19 experiences (see Table 1). Below is a summary of each country.

***Italy*.** By April 2020, Italy became the European epicenter of the corona virus (Winfield, 2020). Observers of Italian politics during the pandemic suggest that the experience with Covid-19 further contributed to a surge in nativist–populist sentiment, aided by a view that immigrants spread the virus (De Maio, 2022, para. 7). Italy's political and media systems have historically been closely tied to each other through the partisan press (Hallin & Mancini, 2004). Although Italy has lower internet penetration rates than other western European countries (Poushter et al., 2018, p. 5), 40% of online Italians use social media to share news; by comparison, the rate is 23% in Norway and 25% in South Korea (Newman et al., 2021, pp. 89, 93, 147), with Twitter occupying a small but important niche in the digital political ecosystem (Vaccari et al., 2015, p. 226).

***Norway*.** In contrast to Italy, Norway had among the lowest mortality rates from Covid-19 in Europe, thanks to widespread testing and limited public resistance to movement restrictions (Nilsen & Skarpenes, 2022). In line with the small, cohesive nature of the country, Norway's media have traditionally taken a pluralistic and consensus-building role (Hallin & Mancini, 2004). Global digital platforms have been met somewhat ambivalently (Syvertsen et al., 2014), with both high adoption rates (Poushter et al., 2018; Newman et al., 2021) and frequent public debates about the effect on the public sphere. Among the concerns is that social media give a greater voice to populist right-wing views, which included some opposition to Covid-19 measures (Mjelde, 2021).

***South Korea*.** In contrast to Italy and Norway, South Korea reversed initially high rates of Covid-19 infection through strict quarantines and isolation wards, testing, and contact tracing (Kim et al., 2022), making South Korea a global model for Covid-19 response (Koo, 2022). South Korea's media system has seen a relatively recent democratization, with a rapid transition from a state-run media monopoly to a mass media market, write Rhee et al. (2011). They argue that the public sphere is still underdeveloped, with South Korean news media often playing an advocacy role in "organizing elite opinions and group interests" rather than offering a voice for civil society (p. 332). As a result, social media use in South Korea is often framed by scholars as alternative avenue for counter-publics – in particular, as a place for progressives to counter the neoliberal views in dominant national media (Choi & Park, 2014; Choi & Cho, 2017). Like in other democracies, South Korea has seen trends toward populism (Shin, 2022) and social division in recent years (Draudt, 2022), though as Lee (2022) writes, Covid-19 has not been a central point of this division.

Table 1. Country profiles

Country	Population	Internet use (%)	Twitter use (%)	Cumulative Covid deaths at time of data collection	English proficiency
Norway	5.4 million	97	17	244 (July 15)	very high; rank 5
South Korea	51.7 million	97	17	295 (July 13)	moderate proficiency; rank 37
Italy	60 million	70	18	35,042 (July 13)	moderate proficiency; rank 35

Sources: World Bank Data; Hallin & Mancini, 2004; Rhee et al., 2011; Reuters Digital News Report, 2021; WHO Coronavirus Dashboard; EF EPI, 2021 report.

Data and Methods

A total of 450 Tweets were collected from March 15 to July 16, 2020, from Twitter's streaming API using the DMI-TCAT, a tool developed at the University of Amsterdam (Borra & Rieder, 2014).[i] The keywords *covid19* and *covid* (which also picks up "covid-19") were used to select tweets from the live global stream. These keywords are relatively language-neutral – "corona" for example, is spelled differently in some languages, including Norwegian. Even so, it should be noted that the use of Latin characters for data selection may limit the South Korean tweets. The global four-month data collection yielded more than 131 million tweets (N = 131,692,303).[ii]

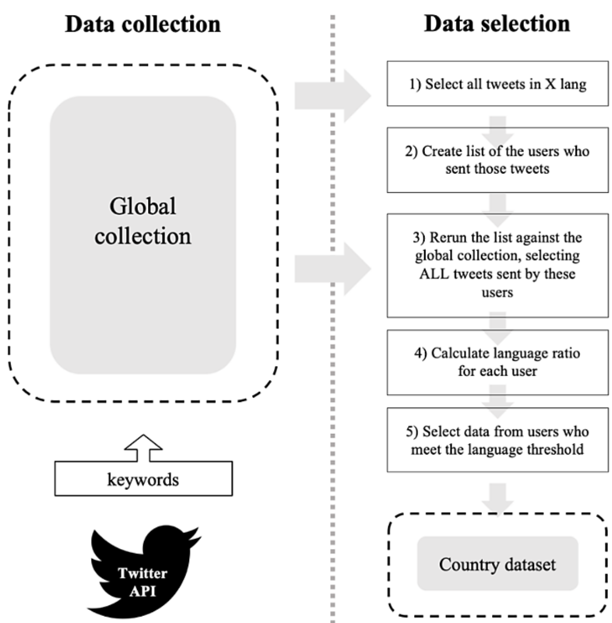


Figure 1. Mediation model for first-generation immigrants

Data selection

A dataset for each country was then created from the global collection. The primary method of identifying the country-based users was language, with geolocation used to validate the method. The Twitter API provides metadata about each tweet including the language of the tweet text. Thus, for each country, selection began by identifying tweets matching the national languages, lang = 'no' for Norwegian, lang = 'ko' for Korean, and lang = 'it' for Italian. From these tweets, a master list of the users was created: 320,258 for Norwegian, 405,647 for Korean, and 3,345,063 for Italian. Following this, all the users' tweets – that is, those in any language – were retrieved from the global collection. (See Figure 1.)

However, this method alone was found to be insufficient. First, algorithmic identification of the tweet language is not perfect and will misidentify tweets from related languages. Moreover, it was discovered that spam or automated accounts often tweet in many languages. Because this method uses all the tweets collected from each user, prolific spam accounts can have an exponentially distorting effect on the data. For example, one user with 260 followers contributed 13,000 tweets to both the Norwegian and Korean language sets because they tweeted once in each language. Thus, an additional language threshold was established.

This threshold was determined by comparing the results against the geotagged data and the most frequent locations that appeared in the data (see Figure 2). A 10% threshold was reached for the Italians and Koreans, meaning that 10% of each user's tweets had to be in Italian/Korean. In the case of the Norwegian users, it was discovered that the 10% threshold still led to a significant number of Danish, Swedish, and German users due to linguistic similarities. Thus, for the Norway dataset, an additional threshold was added, removing any users who tweeted in Danish, Swedish, and German more than 50% of the time. The final datasets are described in Table 2.

Network analysis

Network data was then extracted from the datasets based on @mentions and retweets, as well as "via" tweets, which is common when a user tweets an article directly from a news outlet's website.[iii] These interactions form a "tie" between one network "node" (the user tweeting) and another node (the user being retweeted or @mentioned). The network data contains one line for each of these ties, meaning that the

[i] The data collection and storage plan was approved by Norwegian Center for Research Data, which assesses researchers' adherence to Norwegian and European data privacy laws.
[ii] Twitter enforces rate limits on its public API that prevent access to all the available tweets on high-volume queries, so this represents a sample rather than a comprehensive collection.
[iii] Information about likes and quote tweets are only available in aggregate from the Twitter API.

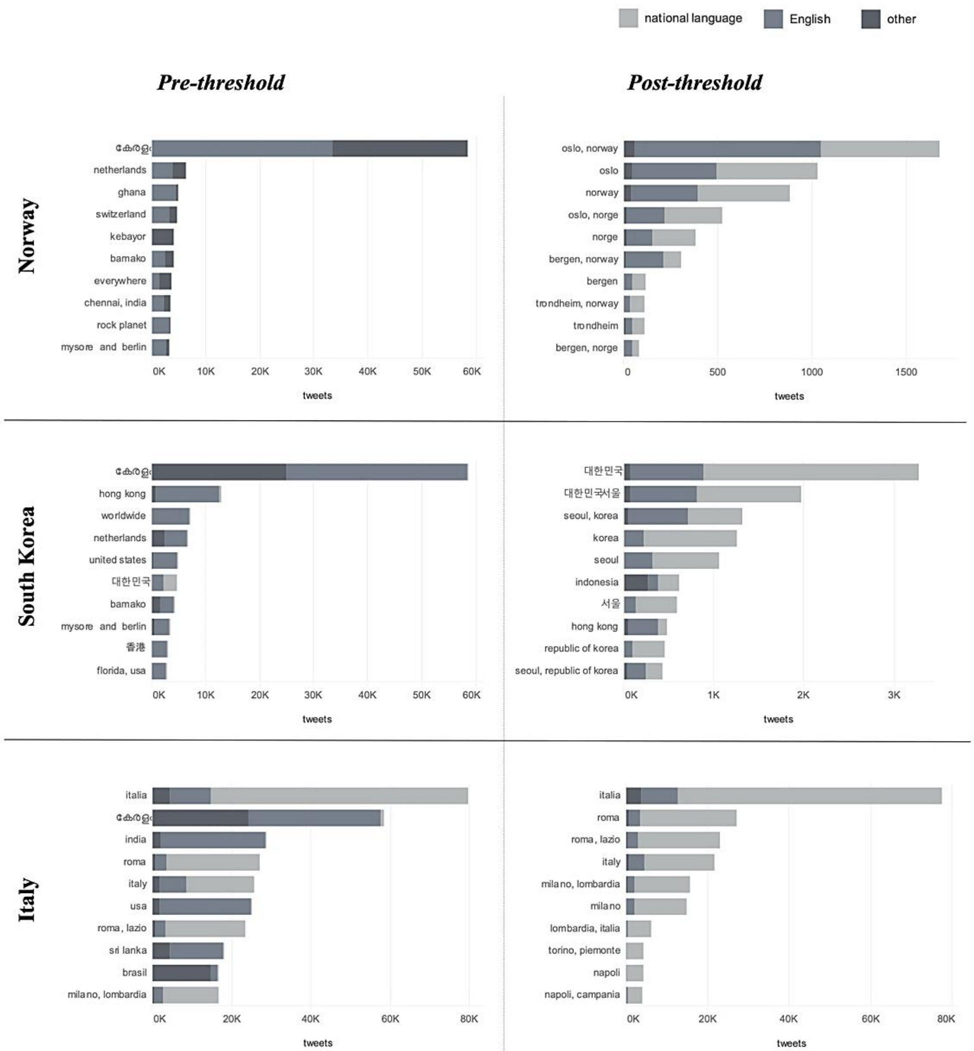


Figure 2. Location validation of language threshold

Table 2. Country datasets

Country	Tweets	Users	Tweets per user	Languages
Norway	16,617	4,367	3.8	45% Norwegian 42% English 13% other languages
South Korea	117,291	43,599	2.7	65% Korean 26% English 3% Indonesian 6% other languages
Italy	1,148,812	169,810	6.8	82% Italian 12% English 6% other languages

nodes in the network include not just the original userbase (those sending the tweets), but also those users @mentioned or retweeted.

The network data was imported into the network analysis software Gephi and visualizations were created using the ForceAtlas2 algorithm (Jacomy et al., 2014). The algorithm works by simulating a gravitational pull between nodes that have ties to each other, resulting in a visual network map that simulates the distances between users based on common ties. The following statistics were then calculated for each network:

- *Modularity*: This measures the tendency of nodes to cluster together, and is calculated by how connected each node's neighbors are to each other. A set of nodes belong to a cluster if the connections among these nodes are more frequent than with others. The modularity algorithm developed by Blondel et al. (2008) produces a figure between 0 and 1.

- *Average path length:* A path length refers to the shortest path to get from node A to node B. The average path length describes the average shortest distance between nodes.

- *Diameter:* The diameter is the longest path length in the network (the "longest shortest distance" between two nodes).

- *Closeness centrality distribution:* Closeness centrality refers to the average distance of a node to all other nodes in the network (Himelboim, 2017, p. 6). Graphing the closeness centralities helps show the distribution of importance. A distribution skewed toward 1 suggests the network has a few hubs and many peripheral nodes; the closer to zero, the more egalitarian or decentralized the network is.

In addition, the major "hubs" in the network – the most isible users – were discovered by calculating degree centrality (in-degree) or the number of other users who have @mentioned or retweeted a user.

Findings

In order to identify the utility of multilingual data, each country was initially separated into two languages: the national language (Figure 3-A), and the second largest language group (Figure 3-B). In the case of all three countries, the second largest language is English. The differences are then analyzed. Following this, the full multilingual network is mapped and analyzed (Figure 4-A, B, C). Finally, all three countries are joined together through their English language data (Figure 4-D).

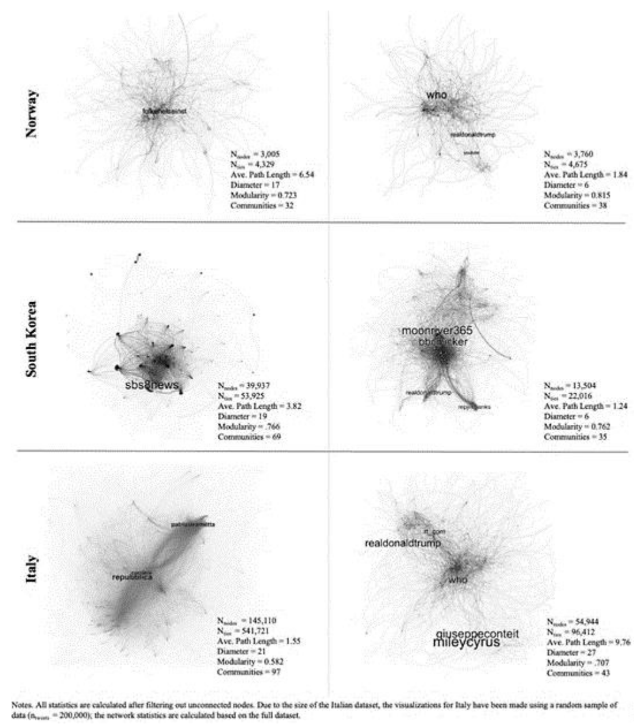


Figure 3. Single-language network map

National language networks

Overall, we see that the networks reflect different types of structures. The Norwegian network (Figure 1-A-Norway) is relatively dispersed, exhibiting a more egalitarian, decentralized structure in which there are few common hubs. Instead, subnetworks are localized around different interests, including universities, politics and government, and sports celebrities. To the degree that there is a central figure, it is the Norwegian Public Health Institute (@Folkeheseinst) and individual health experts.

In contrast, South Korea is more hierarchical, being characterized by what Park and Thelwall (2008) call a "hub-and-spoke topology" (p. 870), in which users are connected to a small number of central actors – in particular, the account associated with the evening news program of the Seoul Broadcasting System (SBS). Farther outside the main graph, we find users around K-Pop accounts. Interestingly, the other hubs are not just familiar elites; a number of individual accounts with modest followings also act as hubs, due to viral tweets (these users are not identified due to European data privacy laws.)

The Italian language map (Figure 3-A-Italy) demonstrates yet another network topology – a polarized network structure, in which the network is largely divided between two large subnetworks (Himelboim et al., 2017, p. 10), a mainstream subnetwork in the center to lower left and an oppositional network in the upper right of the map in Figure 3-A-Italy. The major hubs in the mainstream network are media accounts and politicians, while those in the oppositional network appear to be more grassroots Covid-19 skeptics, such as Patrizia Rametta, a member of the right-wing populist League party (@lega) who was identified as a Covid-19 misinformation "superspreader" by the fact-checking service NewsGuard (Richter et al., 2020). At the time, Rametta had around 38-thousand followers; she has since been suspended by Twitter. Despite this general structure, the modularity level in the Italian network is relatively low (0.582), as is the average path length (1.55) compared with the Norwegian and Korean language networks. This could suggest that the two Italian subnetworks are not highly cohesive, which the visualization also suggests in the relatively long spread of the two sides of the map.

English language networks

The English language networks were then mapped, revealing different characteristics from the national language network structures. In Figure 3-B we see that the English language networks, despite being made up of the same users in Figure 3-A, do not adhere to the same structures as the national languages. Starting with Norway, we see a more centralized, hierarchical network, as evidenced both by the closeness centrality distribution (see Appendix) as well as the network diameter (6) and average path length (1.84). By far the most influential hub in this network is the World Health Organization (@who). However, we also see a subnetwork in the lower right that was not as visible in the Norwegian-language network. In this network, @realDonaldTrump and @YouTube are important nodes; the presence of @YouTube is the result of users sharing English-language videos about Covid-19. Other users in this network (e.g. Russia Today) further indicate that this is an oppositional network.

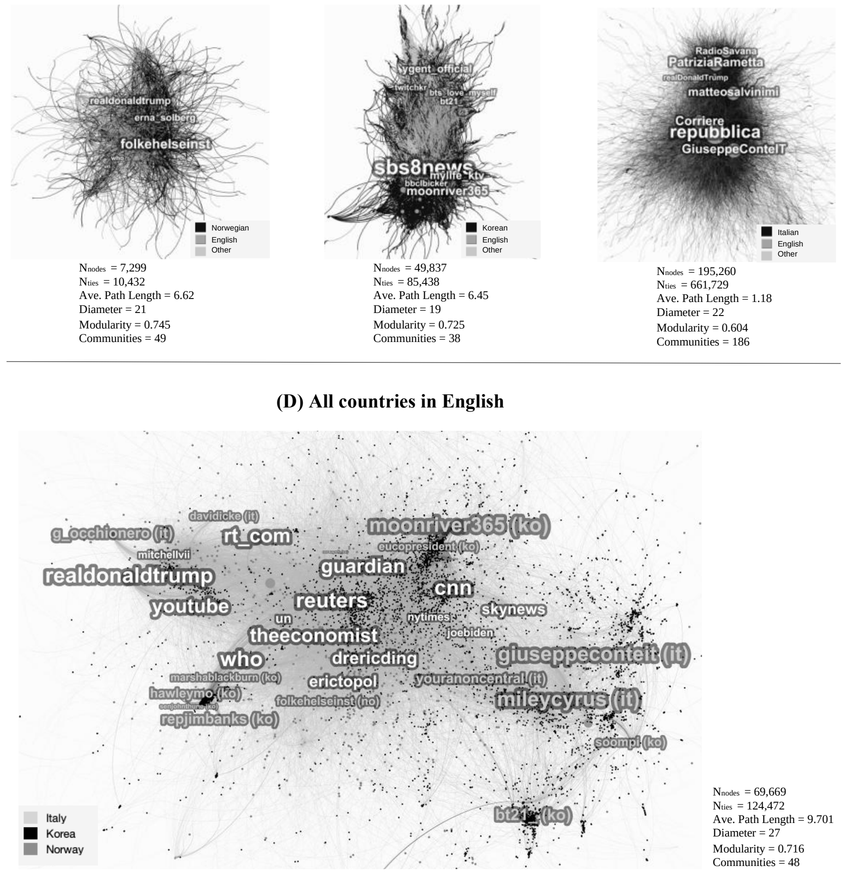
A similar structure emerges in the South Korean English-language network (Figure 3-B-South Korea), which is again different from the national language network. In the lower part of the map, Donald Trump appears along with other conservative figures and the account for the U.S. Armed Forces in South Korea. A separate network in the lower right is focused on other conservative American politicians. K-Pop accounts populate the top of the map. Interestingly, the English-language network is about as modular as the Korean-language network (0.762 vs. 0.766 modularity), yet the distance information travels is lower. This could be due in part to more centralization around a few hubs in the English-language network – and fewer of the sort of viral moments by ordinary users that characterized the Korean-language network. Another unexpected component of South Korea's English-language network is that South Korean President Moon Jae-in appears here as the most influential hub. This will be further assessed in the concluding discussion.

Finally, Italy differs from the other two countries in that its English-language network has a larger diameter and average path length than its national language network. This suggests a less cohesive English language sphere among Italians – that is, they may have fewer common users that they interact with in English, even compared to the already polarized Italian sphere. The high modularity (0.707) and low number of communities also suggest polarized communities.

This network also shows a level of attention to the Italian prime minister not visible in the Italian-language network. It appears that Giuseppe Conte primarily received attention from Italians when he engaged in a tweet exchange with the American pop star Miley Cyrus about the pandemic (Conte, 2020). Meanwhile, the core of the network is structured similarly to the other countries, focusing on mainstream news and health sources, including the WHO. A smaller yet significant subnetwork is made up of Covid-19 skeptics, where Donald Trump is a central actor, as well as British and American fringe figures. This network is not integrated into the main network.

Global networks

Figure 4 (A, B, and C) puts the previously described data in perspective. The visualizations include all languages, which shows the way key hubs are placed in the network map, as



Notes. Figures A-D: All statistics are calculated after filtering for the giant component. Nodes and ties are colored according to the national origin of the user. Due to the size of the Italian dataset, the visualizations for Italy (C) have been made using a random sample of data (n_{tweets} = 200,000), while the network statistics are calculated based on the full dataset. Figure D: The Norwegian and Korean nodes have been resized so that they are more visible relative to Italy. Usernames labeled in white represent major hubs common to all three countries. Usernames labeled in grey are major hubs specific to one country (indicated in parentheses).

Figure 4. Global network map

well as the relationship between the national language and other languages. In the case of Norway, English language tweets are distributed throughout the network, reflecting the fact that 39% of the Norwegian users tweeted in more than one language, typically English. Meanwhile, the Italian network shows a much more peripheral use of English, while South Koreans had whole communities that largely English or Korean. Italy and South Korea had 20% dual-language users and 23%, respectively. South Korea's These appear in connection with K-Pop accounts at the top of the map, suggesting that these may not be Korean users, but rather foreign users who have retweeted enough Korean language tweets about Covid-19 to pass under the language threshold.network is distinctive in its combination of several languages, particularly Thai, Indonesian, and Japanese.

Because English is the shared second language of these countries' Twitter networks, it is also possible to combine the English-language data from each of the countries into one network. In Figure 4-D, the major English language hubs have been labeled. Those shared across the three countries are labeled in white, while those that were only significant in one country are in grey. We see that certain actors, particularly anglophone media, act as common global sources. Star medical experts Eric Ding (@drericding) and Eric Topol also appear there. The WHO and the U.N. are also shared across countries. The global network also features a strong oppositional subnetwork on the left, where Donald Trump and Russia Today are major hubs shared across countries. Yet other English-language hubs are specific to each country. I will discuss these findings further in the next section.

Concluding Discussion

Drawing on previous literature on Twitter networks in health communication (Getchell & Sellnow, 2016; Hagen et al., 2018; Hellsten et al., 2019; Kamiński et al., 2021; Vijaykumar et al., 2018), this paper places health communication about Covid-19 in a wider global context. The methodological approach recognizes two key traits of online information ecosystems: First, the structure of networks influences the flow of health information. Second, these networks are not necessarily nationally bound. In contrast to previous approaches in health communication (e.g., Guidry et al., 2019; Hagen et al., 2018; Hellsten et al., 2019; Vijaykumar et al., 2018), this approach considers Twitter users' consumption of material from both inside and outside the national sphere by using multilingual data. It is argued that in the age of digital online networks, such an approach gives a more comprehensive view of the information ecosystems in which people find health information.

In response to RQa, regarding the differences between national and multilingual networks, the findings suggest that users' networking patterns within their national language sphere to not necessarily match patterns within a global context. While the national language networks bore resemblance to understandings of the national media systems in Norway, South Korea, and Italy, these patterns did not hold up when looking at the same users' English-language networks. In the case of Norway in particular, the relatively egalitarian national network became more hierarchical and modular at a global level.

Additionally, in all three countries, the use of multilingual data made more evident the existence of oppositional network structures. In the case of Norway and Italy, these were oppositional networks that relied heavily on fringe actors. Hubs in these networks (RQb) include low-information sources identified by Yang et al. (2021), notably @realDonaldTrump, Russia Today, and Zerohedge.com. Among the most popular tweets from Donald Trump was his claim that hydroxychloroquine was effective against Covid-19 (Blevins et al., 2021). Other important hubs in the oppositional network include the British conspiracy theorist David Icke and conspiratorial content on YouTube, echoing Choi et al.'s (2021) findings about the use of YouTube for health information, and misinformation. One of the most retweeted YouTube videos in the data claimed that the president of Ghana had endorsed a theory that Covid-19 had been planned by global elites (see Goodman, 2020). Multilingual data also reveals the role of national figures who tweet mainly in English, such as Giulio Occhionero, an Italian financial analyst and hacker with populist views who was arrested for hacking the email accounts of major Italian government officials (Scherer & Giorgio, 2017).

This kind of opposition was less pronounced in South Korea where the multilingual data revealed other types of subnetworks. First, we see that South Korean users are connected to global K-Pop fan communities, highlighting K-Pop groups' role as arbiters of Covid-19 information inside and outside the country. Second, and more unexpectedly, the data show a peripheral subnetwork connected to Republican members of the U.S. Congress (see Figure 4-D). I initially wondered if this subnetwork indicated a problem with the method. However, further inspection shows that these politicians were vocal on Twitter in blaming China for Covid-19 – a stance that attracted support from users in South Korea (and to some degree Italy).

Yet some of the most important English-language hubs are not American, nor even foreign: they are domestic. The heads of state in Italy and South Korea appear as major hubs only through the multilingual data. The finding does not hold up for Norway's prime minister; however, the Norwegian public health authority, Folkehelseinstituttet, was among the top English language hubs for Norwegians. This suggests that English language content from national authorities, ostensibly meant for the global audience, is also highly consumed and shared by the domestic audience, lending empirical support to Guidry et al.'s (2020) observation that health officials must learn to communicate both locally and globally. Though perhaps as suggested by Park et al. (2022), it doesn't hurt to involve an international pop star like Miley Cyrus.

The findings show there is not one global information sphere – each country exhibited a nationally-specific relationship to English-language information. However, combining the three countries did identify certain common global hubs (RQc). In contrast to previous findings about global health information (Househ, 2016; Yang et al., 2021), the most important news outlets are not American brands (with the exception of CNN). Moreover, international bodies such as the WHO and the U.N. were important players. Where American influence was more visible was in the oppositional network, where Donald Trump seemed to act as a major hub around which the cluster formed. Additionally, American medical experts Eric Ding and Eric Topol were also highly influential, rivalling the WHO and U.N. and pointing toward a role for personalized, celebritylike expert during a health crisis (Kamiński, 2021; Mancini, 2020).

Overall, the findings suggest that health communication researchers and practitioners seeking to track information flows on Twitter need to consider not only the communication that takes place in the national sphere. Twitter users blend national and international health messages together, engaging in the same space with both the local public authority and the international or foreign health expert. While these sources may be aligned in some matters, this may also produce different frames of reference than health communicators anticipate. For example, Eric Ding claimed in a tweet in July that public health experts "agree" that masks should be mandatory for children in school (Ding, 2020). This was at a time when experts at the Norwegian Folkehelseinstituttet had determined masks were not necessary in schools. Thus, contextual differences may make it difficult to determine what an "anti-science" message is. Approaches that recognize these practices may enable researchers and practitioners to more effectively identify key sources of information and influence, and potentially anticipate contradictory sources in times of crisis.

The findings from each country also reveal that network structures are different in different languages, with English appearing to be more polarized than the national language. This may be especially concerning for small countries like Norway, where there was an especially strong contrast between the egalitarian structures of the national language and the hierarchical English-language network. The findings suggest that Norwegians' English-language networks had more distinct subcommunities – and that those in the oppositional community were especially engaged with sources from outside of Norway. This may be true for other small, highly globally connected countries, and suggests a need for national public health officials to be embedded in the same multilingual networks.

While the method demonstrated here could be used for other globally relevant issues, it is especially apt for disease communication. Unlike natural disasters, contamination, or economic and political upheaval – whose causes and remedies tend to be closely tied to the local/national context – the effects and treatments of disease are relatively universal. Such global transferability has long been the basis for formal international information sharing among public health agencies (WHO, 2007). Likewise, digitally networked publics now have the ability themselves to virtually cross borders and gather information in the face of health crisis.

Limitations and further research

This research is limited by the keywords, which did not capture all the relevant tweets, particularly from South Korea. Research into global health information may be better served by using multilingual keywords. It is also worth remembering that Twitter is a niche platform, and the users who tweet in multiple languages are likely also among the elite compared with the general population of most countries. So, while Twitter is politically influential, its userbase should not be seen as representative of national populations. Nevertheless, it would be interesting to see more research on the role of bilingual users in health communication networks. More research is also needed on what kinds of content crosses borders, and how users make meaning of this content in a different cultural context (Choi & McKeever, 2020). Additionally, in this case, users were able to be established through national languages; that is, most speakers of Norwegian, Korean, and Italian are in Norway, South Korea, and Italy, respectively. However, language is not a perfect proxy for geography: Italian is spoken in several neighboring countries, South Korea has a sizeable Korean diaspora, and Norwegian is similar to the other Scandinavian languages. Language in this case provides a certain level of centering around a particular country. However, future research might employ geolocation more extensively; this would be especially important for studying speakers of Spanish, Portuguese, Russian, or Arabic, for example, which are spoken in many different national contexts.

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