



Research Article

Ibuprofen Narratives in Five European Countries During the COVID-19 Pandemic

We follow the trajectory of the unverified story about the adverse effects of using Ibuprofen for treating the Coronavirus disease 2019 (COVID-19) on Twitter, across five European countries. Our findings suggest that the impact of misinformation² is massive when credible sources (e.g., elected officials, mainstream media) participate in its propagation; yet, they also imply that crisis communication management has a local scope given the greater reach and impact of regional channels in the spread and countering of misinformation. These patterns reveal both the global and local dynamics involved in the spread of misinformation. However, they are based on Twitter data, which might cast doubt on their generalizability. We discuss these and other limitations of the study as well as some of their implications for future research in the closing section of this article.

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Research questions

- How did the narrative about Ibuprofen and COVID-19 circulate across these five European countries? Did misinformation spread following a global or a local dynamic? Where was misinformation more prevalent within these territories?
- What kind of users helped promote this information? What role did credible sources play in propagating misinformation?
- What role following official governmental accounts played in protecting citizens against unverified messages? In particular, was following official governmental accounts effective for countering this information?

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² We use the term misinformation to refer to false or inaccurate information that is shared accidentally. In contrast, we use the term disinformation when false or unverified information is shared deliberately.

Essay summary

- We use Twitter data to understand how unverified information related to Ibuprofen was promoted by credible sources and travelled across five European territories for two weeks— from March 11 to March 25, 2020.
- We find that the impact of misinformation in a particular territory is remarkably superior when regional credible sources are key players in promoting unproven narratives.
- Crisis communication management has a local scope. Despite being a global pandemic, regional channels had a greater reach and impact among citizens in their territory.
- The degree of contagion between credible sources is very high, which causes an exponential increase in the reach of their messages. In the case studied, media played an important role as propagators, both within and across territories.
- Following official sources —when they publish verified information—reduces the likelihood of propagating misinformation and is a good means to be better informed.
- During the pandemic, social media companies tailored their policies to heal the information in their environments, but they face new challenges, as credible sources (from verified accounts) are responsible for disseminating misinformation.

Implications

In the first months of 2020, the COVID-19 pandemic caused one of the most dangerous global health crisis of our era. As a novel disease, there was great uncertainty about how to fight it. The World Health Organization (WHO) tried to coordinate a global response; the global scientific community conducted multiple research efforts on how to treat and cure the disease. Although information about the preliminary results of the studies soon began to emerge, the outcomes were inconclusive, and different information on disease treatment was reported in certain regions. Knowledge gaps together with an increasing demand for information fostered the appearance of numerous narratives not always based on proven facts. The vast amount of unproven information circulating during this period is reflected in the WHO's declaration³ of the infodemic days before declaring the health pandemic.

In this article we focus on one instance of an alternative narrative appearing in Germany and spreading across different European countries from March 11-24. This narrative advocated avoiding the use of Ibuprofen to treat COVID-19 and even warned that its consumption increased mortality in patients, when in fact no existing scientific evidence supported any of this. What made this story distinct is that the French health minister, Olivier Veran, was one of its main promoters. On March 14th, he posted a tweet⁴ (Figure 1) advising patients against the use of Ibuprofen because preliminary research pointed to associated risks. This message triggered an immediate reaction that greatly extended its reach.

³ <https://www.who.int/dg/speeches/detail/munich-security-conference>

⁴ <https://twitter.com/olivieveran/status/1238776545398923264>



Figure 1. French health minister, Olivier Veran, tweet against ibuprofen (ibuprofène). Tweet translation: taking anti-inflammatory drugs (ibuprofen, cortisone, ...) could be a factor in aggravating the infection. In case of fever, take paracetamol. If you are already taking anti-inflammatory drugs or in case of doubt, ask your doctor for advice.

Comparable narratives in other territories (e.g., US, Brazil) include the use of hydroxychloroquine as a possible cure for the disease, which were also promoted by top elected officials (e.g., Trump, Bolsonaro). Studying misinformation about treatments for any disease is important, especially when reliable sources play a key role in promoting false information, because of the impact it may have on people's safety and health (Starbird, Arif, and Wilson, 2019).

In this research we used Twitter data to trace the public path of the Ibuprofen story. We discovered that this story originated in a WhatsApp voice message. Due to the private nature of instant messaging applications, we were only able to trace the narrative from the time it jumped from WhatsApp to Twitter.

Based on digital trace, we were able firstly to study where the story started and how it spread from the country of origin (Germany) to users in the Netherlands, France, and finally Spain and Italy. Next, we analyzed the role that credible sources, such as political representatives and respected media, played as promoters of misinformation. Finally, we used the case of Catalonia (a Spanish region for which we had data) to examine the effect that following (local) official sources had on the likelihood of debunking false information.

Overall, this study has three real-world implications. The first implication relates to the role of trustworthy sources in the spread of misinformation. Using official channels and reliable sources to obtain information is recommended as one of the basic measures, to globally combat misinformation. But what happens when these sources are the ones that broadcast unverified information? We show that this might have catastrophic consequences, particularly in the context of a health crisis, for at least two reasons. First, due to their extreme visibility and the implicit trust given to the information they convey, credible sources can have a massive impact on spreading misinformation; second, because turning to credible and expert sources is deemed as one of the few efficient strategies citizens can rely on to combat misinformation (Vraga et al., 2017).

Previous work has shown how difficult it is to correct misperceptions (Lewandowsky et al., 2012; Nyhan

& Reifler, 2010) and has proposed several ways in which citizens might fight misinformation (e.g., Swire-Thompson & Lazer, 2020; Tully et al., 2020). Yet, these studies address debunking in general, not when official sources are the main channels disseminating misinformation. When experts and public officials are involved, there are two paths to combat misinformation. Firstly, it has proved efficient that the same reliable sources correct the information with messages prepared to be shared in social media (Wardle & Derakhshan, 2017). In the case of the false narratives related to ibuprofen, the official sources that spread the misinformation did not correct themselves. However, other trustworthy and expert sources (e.g., WHO) corrected it, albeit without much success, because despite the correction misinformation continued to spread. Secondly, we can also combat misinformation coming from trustworthy sources by better educating the public on information consumption. Improving the information environment by enhancing skills such as critical media literacy, to encourage a critical attitude towards the information we consume (Buckingham, 2019), news literacy, to understand the press business (Tully et al., 2020) and transmedia literacy skills, to figure out how multiple sources fit into the information environment (Scolari et al, 2018).

A second implication of this study relates to the scope of communication in global health crisis. Even though our study shows that the degree of contagion among credible sources is very high, it also shows that communication in emergency crises has a regional dimension. This may multiply opportunities to combat misinformation if enough official sources at the local level are not disseminating unproven information. In particular, our study shows that when these sources are not promoting misinformation, following local official channels decreases (increases) the probability of spreading (debunking) misinformation by 60% (finding 4). Thus, in unaffected countries (or regions), citizens may have ways of fighting misinformation by resorting to official sources of information locally. The downside, however, is that in infected countries the local scope of communication may lock citizens in contaminated environments and leave them completely unprotected against misinformation.

A final implication of this study concerns the accountability of digital platforms in correcting misinformation within their ecosystems, as much of the unproven information was spread from verified accounts. During this pandemic, digital platforms took steps to promote healthy conversations, encouraging, among other measures, that information be obtained from credible sources. However, in this case, platforms faced a new challenge for which they had no solution: seemingly credible sources were actually the ones promoting misinformation from their verified accounts. This represents a real challenge, because the kind of verification that platforms exercise to promote healthy conversations consists on authenticating the accounts (i.e., verifying that the content comes from the person who purports to come) not on checking the veracity of the content they publish. In the case studied, the platforms did not take any action against messages from credible sources promoting misinformation until days later, when political leaders in the United States and Brazil disseminated similar unproven narratives, prompting the platforms to take stronger action, blocking these messages from their ecosystems.

In a context where multiple unverified narratives circulate on their platforms, social media companies cannot stay on the sidelines; they need to play a bigger role to guarantee a healthy information environment, especially during a pandemic since inaccurate information can potentially have very harmful consequences.

Findings

Finding 1: The spread of misinformation in crisis communication has a regional dimension.

Our research shows that once the story gained traction, mainly after the French health minister's tweet, it continued to be transmitted between countries, even though different particular users and credible

sources across countries denied the veracity of the information. Figure 2 presents the number of tweets related to the narrative from March 11 to 24, showing that the narrative is prior to the tweet of the French health minister, although it becomes truly relevant after this tweet is issued, on March 14. Each color represents a language⁵. In Panel A in Figure 2 we show the total number of daily publications per language; in Panel B, the percentage of daily tweets per language. Note that Panel B maps tweets by language on an equal scale, which eliminates the huge differences in number of daily tweets between the period previous to the French minister’s tweet (11-14) and the period following this tweet (14-24).

This reveals two aspects of the dissemination of information. First, despite the impact of the message of the French minister's tweet (see Panel A), the message is disseminated at different rates in each region. In Panel B, we can observe how the conversation gains traction on different days in different territories, the 14th especially in France, Germany and Spain, later the Netherlands and Catalonia are added, and we see that in Italy it was relevant from March 21st to 23rd.

Second, adding to previous research, we uncover a regional dimension in the spread of misinformation, showing that despite denials, alternative stories continued to circulate (Wang & Zhuang, 2018; Vosoughi et al., 2018). In our research we found that, although supragovernmental bodies such as the WHO^{6 7} and the European Medicines Agency⁸ ruled out the information, the speed at which false information spreads was not reduced until official channels in each region denied the information. This indicates a strong regional dimension in the dissemination of information.

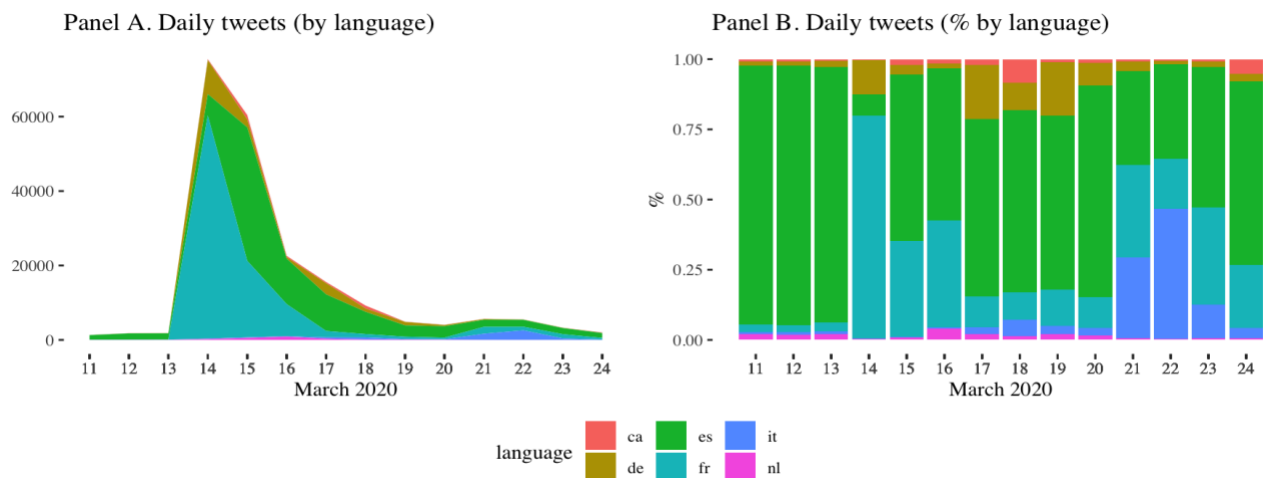


Figure 2. Tweets per language: Absolute (Panel A). Percentual (Panel B).

Finding 2: Misinformation was predominant in the territories where credible sources promoted it.

Figure 3 shows the fate of Ibuprofen’s alternative narrative by country. Our set includes five European countries. It also includes one region (Catalonia) that will be used to test the “debunking” effect of following governmental sources. Dots are represented in different colors according to whether the message contains verified information (=TRUE, blue) or not (=FALSE, red). The shape of points represents

⁵ ca for Catalan, de for German; es for Spanish; fr for French; it for Italian and nl for Dutch.

⁶ <https://twitter.com/WHO/status/1240409217997189128>

⁷ <https://twitter.com/WHO/status/1240409220916432899>

⁸ <https://www.ema.europa.eu/en/news/ema-gives-advice-use-non-steroidal-anti-inflammatory-covid-19>

the authorship according to types of author: credible sources (rounded); fake credible (square); generic (triangle); and profiteers (cross).

In France, where the message was promoted by a credible source, the impact of misinformation was the greatest of all studied. This can easily be seen in Figure 3, where all messages in French are colored in red, indicating that they were all infected. In this country, the minister of health promoted the message shortly after the narrative first publicly surfaced in its territory. A few instances later, other reliable sources, such as the media, reported this information without denying it, which helped to further convey the message. Such was the effect of credible sources' posts in this region—that infected information went completely unchecked with no single popular message denying the unproven information (as all the dots in red indicate).

In contrast, in the country of origin, Germany (de), the story followed a very different path. We traced the origin of the alternative narrative in this country, where it flowed through WhatsApp as a voice message. It was forwarded to different users who helped with its dissemination (the red dot shortly before March 15). As it was not possible to identify the author, the narrative didn't gain credibility and the global conversation essentially consisted of denying and making jokes about it (all blue dots around March 15). Days later, between March 17-19, when the narrative gained strength in other territories, it was debunked again (blue dots during this period). No further outbreaks occur. In short, we observe how misinformation was predominant in the regions, especially France, where reliable sources (squared dots) spread the message. Additionally, the populations' trust in official sources meant that no message refuting the misinformation had much impact.

The other studied territories lie in between these two extreme cases, by combining messages that are infected with messages that are not. The Netherlands was the country where the message first jumped, harmlessly, into the public sphere, due to geographical proximity. In Spain, Catalonia and Italy, the media and journalists were the first to report the misinformation, citing the French minister's statements. In Spain and Catalonia, we observe generic users, with less reach, denying information from the very moment the media covered it. In all the territories on the 18th a second wave appears; especially in Spain, Catalonia, France and Italy the narrative obtains a large reach. In these countries, between 18-19th the message is debunked again. In spite of this, in Italy the story circulated again strongly between the 20th and the 23rd.

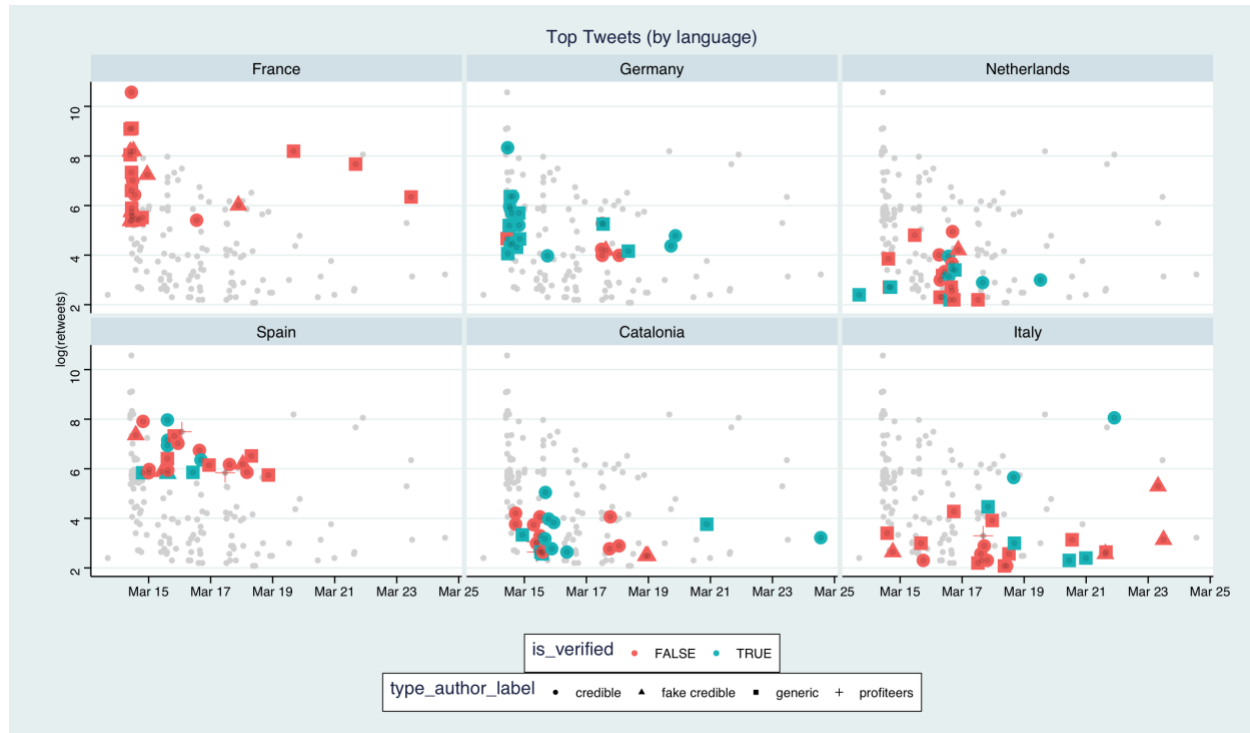


Figure 3. Top tweets by language, truthfulness and author type.

Finding 3: Credible sources have a critical role in information dissemination.

To assess the role of credible sources involved in the trail of contagion, we code tweets according to four categories of actors: credible sources, fake credible, generic users, and profiteers. Following other studies⁹ we distinguished between credible sources, official and verified accounts where it is advised to obtain security and health information (e.g. official governmental accounts, elected representatives, mainstream media and reputable journalists). Fake credible, in this case, influential accounts in matters other than health and safety, such as celebrities or social media influencers; generic users (common users) and profiteers, users who want to benefit from the misinformation. As expected, each region's behaviour was different depending on whether there were reliable sources promoting the message.

Among the four categories of authors, we found that most misinformation messages were written by credible sources (see Table 1 and Table 2). We found a dangerous information connection in which trustworthy sources quickly infected each other, first with the local media reporting the misinformation of the French Minister, and then with media in other regions reporting based on information from the French media. Within this category it was remarkable how in Germany we did not find any relevant message from reliable sources promoting misinformation (Figure 3). All messages with impact from credible sources debunked the narrative. Misinformation promoted by truthful sources is especially dangerous because, as trusted sources, people have a lesser degree of reflection and tend to believe the recommendations without question.

Generic users follow credible sources as the author type with most tweets. The fact that these users did not represent the largest category shows the uniqueness of this case, in which credible sources were

⁹ <https://www.bellingcat.com/news/2020/03/25/the-coronavirus-disinformation-system-how-it-works/>

the main distributors of misinformation. Usually, generic users have a shorter reach and a smaller radius of influence than the other type of users. In spite of this, as they are the largest group, they play an important role in the propagation and influence of information in the closest circles of acquaintances. Following Generic users as author type are Fake credible authors (e.g., celebrities), with 17 tweets. Although this category publishes a smaller number of messages (17) it represents a great threat due to the large visibility and power of connectivity of Fake credible authors, like celebrities. Indeed, other studies (e.g., Nielsen et al.,2020) have found that celebrities have played a significant role in the propagation of unproven information during the Coronavirus pandemic.

At last, we find a small group of profiteers (5), mainly represented by politicians from the opposition, which tried to take advantage of disinformation campaign to attack the national government. The few profiteers concentrate on the more politically divided southern European countries as Table 2 shows. It is especially in Spain that the profiteer action achieves a greater scope promoted by a member of the European Parliament from a far-right party¹⁰.

Table 1. Number of tweets containing misinformation by author type.

Author	Tweets	%
Credible sources	41	39,6
Fake credible	17	16,8
Generic	38	38,6
Profiteers	5	4,95
Total	101	100

¹⁰ <https://twitter.com/hermanntertsch/status/1239872228533186600> tweet was deleted by the author a posterior when it was already retweeted 343 times, with an estimated reach of 665,932.

Table 2. Number of tweets containing misinformation by author type detached by language.

France		Germany		Netherlands	
Author	Tweets	Author	Tweets	Author	Tweets
Credible sources	5	Credible sources	4	Credible sources	7
Fake credible	6	Fake credible	1	Fake credible	1
Generic	14	Generic	1	Generic	9
Profiteers	0	Profiteers	0	Profiteers	0
Spain		Catalonia		Italy	
Author	Tweets	Author	Tweets	Author	Tweets
Credible sources	8	Credible sources	11	Credible sources	6
Fake credible	3	Fake credible	0	Fake credible	4
Generic	5	Generic	2	Generic	9
Profiteers	2	Profiteers	2	Profiteers	1

Finding 4: People who follow local official accounts promote less misinformation and debunk it more.

As a final step, we analyzed the informational impact of following official sources that shared valid and confirmed information for the region of Catalonia (Spain). For this analysis we have classified tweets according to (1) whether or not users followed any of the most important official accounts¹¹ participating in the conversation at that time in Catalonia, and (2) whether or not the messages disseminated were truthful (Table 3).

Table 3 presents the results. It shows that among those Catalan users who contributed to disseminating unverified information (1099), the majority (702, or 64%) did not follow official sources at the time of publication. Indeed, 2 out of 3 untruthful messages came from users not following official accounts. In contrast, among those who shared messages contributing to debunk misinformation (302), the vast majority (257, or 85%) was following official channels, compared to a minority who was not following (45, or 15%).

¹¹ Channels with crisis and health related information: @gencat (Catalan), @salutcat (Catalan), @emergenciescat (Catalan), @sanidadgob (Spanish). More details on methods section.

Table 3. Number of Catalan users by infected and following official accounts. Below we include the percentage for rows.

	Follow	No follow	Total
Infected	397	702	1099
%	36	64	100
Not infected	257	45	302
%	85	15	100
Total	654	747	

After running a simple logistic regression, we estimated the probability of sharing misinformation when users did not follow official accounts in almost 70%, while following these official channels decreased this probability by almost 60% (results are reported in the supplementary material). Although basic, this analysis suggests that following official sources, which share credible information, is a good means of encouraging healthier conversations with verified information, which help preserve people's safety and health.

Methods

In this case study we have explored how alternative narratives about Ibuprofen travelled through different European territories in the context of the COVID-19 global pandemic. To investigate this case, we have relied on data collected from Twitter API using R and the rtweet library (Kearney, 2019). Starting on March 11, and until March 28, 2020, we captured (N= 809,072) tweets using one of the three following words: "ibuprofen," "ibuprofeno," or "ibuprofene." Thus, our data has been selected using relevant keywords (Jungerr, 2016,p. 82). Applying social network analysis, we identified the center of the conversation in five European territories: Germany, France, Spain, Italy and the Netherlands. More details related to data gathering and filtering can be found in the supplementary material.

Once the main sample was established and the trace of the story understood, the next step was to measure the social impact of reliable sources and other categories of authors in the spread of alternative stories. We used a reduction technique to focus on the main conversation (Borge-Holthoefer & González-Bailón, 2017). We filtered the top 25 messages by reach for each language. Then we manually checked that they were written in the corresponding language and we classified them into messages that contained misinformation, messages that debunked misinformation and those that were unrelated. We proceeded by excluding the unrelated messages, selecting the next message according to its impact written in the same language, until we obtained the 25 most relevant messages for each of the six territories to be studied. We were left with 152, as there were two languages with 26 tweets, since two messages had the same impact.

In the next step, we further reduced the scope of study. We focused our attention on the Spanish region of Catalonia and measured the impact of misinformation in this region. The reason for including Catalonia is twofold. First, it allowed proving further our point that the dynamics of misinformation in global health crisis have a local scope; second, we were interested in measuring the influence that official government channels had on misinformation demystification in this region. Catalonia had the additional

advantage of having a regional language of its own¹², allowing to study the dynamics of misinformation for a sample of users located at the sub-country level. To conduct this analysis we gathered Twitter followers from official accounts managing the crisis in the region¹³. We applied epidemiology techniques and classified the Catalan users of the main conversation according to whether or not they followed the official channels, and their role in spreading misinformation (promoters or debunkers). From this classification, we were able to estimate the behaviour of each group of users.

Limitations and Robustness

The use of these techniques has helped uncover interesting patterns concerning the global and local dynamics involved in the spread of misinformation. However, to assess the significance of these patterns several caveats are in order. First, this study is based on a convenient sample of Twitter users for most of which – as is common in studies using this kind of data – we lack relevant demographic information (Golder and Macy 2014). This might raise concerns about the generalizability of our findings. Twitter data may be subject to several shortcomings stemming from biases in representativeness and sampling (Barberá and Rivero 2015), which might limit the potential for generalizing findings to the general population. In turn, problems of representativeness cannot be corrected in the absence of demographic information (Barberá and Steinert-Threlkeld 2019). Although this is an important limitation, processes of information contagion count among the many behaviors that are less sensitive to non-representative samples (Barberá and Steinert-Threlkeld 2019).

A second and perhaps more important caveat concerns causal issues. Although we uncover a strong correlation between the publication of unverified information by credible sources and the spread of misinformation this should not be confused with causation. In other words, we should not conclude from our findings that the spread of misinformation following the tweet of the French Health Minister was the result of “contagion” not of “selection” (for example, many influential sources in France, including the French Health Minister, may have tweeted about the unverified Ibuprofen narrative reflecting a broad social consensus in this country over this matter). In order to separate contagion from selection and to investigate the causal effect of credible sources’ influence in misinformation propagation, future studies should use more appropriate research designs such as randomized controlled experiments in virtual or physical labs (Golder and Macy 2014).

Aside from these, other limitations of this study concern the connections with the offline world and additional data restrictions. Even though social media has been a widely used media during this crisis it has not been the only media citizens have relied on to get information. Citizens have also turned to mainstream media, particularly to broadcasting media (Nielsen, Fletcher, Newman, Brennen, & Howard, 2020) as a widely shared media to get information about coronavirus and thus have had other opportunities to debunk misinformation beyond social media.

Finally, in this study we have only been able to trace the Ibuprofen story once it went public, although we know that much of the misinformation circulates through instant messaging (IM) applications. In this

¹² The official languages of Catalonia are Catalan, Spanish and Aranese. Due to limitations in the data provided by Twitter we could not separate those messages from Catalan users written in Spanish. So we used the language variable to reduce our sample, even knowing that we were not studying all the Catalan users involved in the conversation.

¹³ <https://twitter.com/genecat> (Catalan)

<https://twitter.com/emergenciescat> (Catalan)

<https://twitter.com/salutcat> (Catalan)

<https://twitter.com/sanidadgob> (Spanish)

particular case, the story started with a WhatsApp voice message. Due to the privacy characteristics of these applications, wherein the messages are encrypted, it is not possible to quantify their role in the spread of misinformation. Despite this, these campaigns, when they gain traction and reach, jump into the public sphere, usually via Twitter, and it is from this point that we can study their behaviour.

Bibliography

- Bastian, M., Heymann, S., & Jacomy, M. (2009). Gephi : An open source software for exploring and manipulating networks,2. International AAAI Conference on Weblogs and Social Media.
- Vraga, E. K., & Bode, L. (2017). Using expert sources to correct health misinformation in social media. *Science Communication*, 39(5), 621-645.
- Barberá, P., & Rivero, G. (2015). Understanding the political representativeness of Twitter users. *Social Science Computer Review*, 33(6), 712-729.
- Barberá P., & Steinert_Threlkeld, Z. (2019). How to Use Social Media Data for Political Science Research, in Curini, L., & Franzese, R. (eds) *The Sage Handbook of Research Methods in Political Science and International Relations*, London: Sage, 2019.
- Borge-Holthoefer, J., & González-Bailón, S. (2017). Scale, Time, and Activity Patterns: Advanced Methods for the Analysis of Online Networks. In *The SAGE Handbook of Online Research Methods* (pp. 259–276). 1 Oliver’s Yard, 55 City Road London EC1Y 1SP: SAGE Publications Ltd.
<https://dx.doi.org/10.4135/9781473957992.n15>
- Buckingham, D. (2019). *The media education manifesto*. Cambridge, UK: Polity Press.
- Golder, S. A., & Macy, M. W. (2014). Digital footprints: Opportunities and challenges for online social research. *Annual Review of Sociology*, 40, 129-152.
- Jungherr, A. (2016). Twitter use in election campaigns: A systematic literature review. *Journal of Information Technology & Politics*, 13(1), 72-91.
- Kearney, M. (2019). rtweet: Collecting and analyzing Twitter data. *Journal of Open Source Software*, 4(42), 1829. <https://joss.theoj.org/papers/10.21105/joss.01829>
- Lewandowsky, S., Ecker, U.K.H., Seifert, C.M., Schwarz, N. and Cook, J. (2012). “Misinformation and Its Correction: Continued Influence and Successful Debiasing”, *Psychological Science in the Public Interest*, Vol. 13 No. 3, pp. 106–131.
- Nyhan, B. and Reifler, J. (2010). “When Corrections Fail: The Persistence of Political Misperceptions”, *Political Behavior* Vol. 32 No. 2, pp. 303-330.
- Scolari et al., (2018). *Teens, media, and collaborative cultures: exploiting teens' transmedia skills in the classroom*. Barcelona: Universitat Pompeu Fabra.
- Starbird, K., Arif, A., & Wilson, T. (2019). Disinformation as collaborative work: Surfacing the participatory nature of strategic information operations. *Proceedings of the ACM on Human-Computer Interaction*, 3(CSCW), 1-26.
- Swire-Thompson B., & Lazer D. (2020). Public Health and Online Misinformation: Challenges and Recommendations. *Public Health and Online Misinformation: Challenges and Recommendations. Annual Review of Public Health* 2020 41:1, 433-451.
<https://doi.org/10.1146/annurev-publhealth-040119-094127>
- Tully, M., Vraga, E. K., & Smithson, A.-B. (2020). News media literacy, perceptions of bias, and interpretation of news. *Journalism*, 21(2),209–226. <https://doi.org/10.1177/1464884918805262>
- Vosoughi, S., Roy, D., & Aral, S. (2018). The spread of true and false news online. *Science*, 359(March), 1146–1151.
- Wang, B., & Zhuang, J. (2018). Rumor response, debunking response, and decision makings of

misinformed Twitter users during disasters. *Natural Hazards*, 93, 1145-1162. <https://doi.org/10.1007/s11069-018-3344-6>

Wardle, C., & Derakhsan, H. (2017). Information disorder: Toward an interdisciplinary framework for research and policy making. (Report No. 162317GBR). Council of Europe. <https://edoc.coe.int/en/media/7495-information-disorder-toward-an-interdisciplinary-framework-for-research-and-policy-making.html>

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Competing interests

One of the authors works for the Government of Catalonia as a public servant.

Ethics

Institutional review for this project was unnecessary as it analyzes only public social media posts and those reproduced in public data archives.

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Appendix

1. Supplementary methods

We started our filtering process with the 809,072 tweets originally captured. The first step was to apply social network analysis methods to overview the public conversations about the story. Using Gephi (Bastian, et al., 2009) we applied modularity class and Hyperlink-Induced Topic Search (HITS) algorithms to visualize the graph of the relationships and communities of users. We identified the core of the conversation in five European territories –Germany, France, Spain, Italy and the Netherlands. In addition, using the time when tweets were created at, we were able to observe the pace and speed with which each community was incorporated into the global conversation.

The next step was to select only the messages from users of these territories. In order to do this, we used the language variable that the same rtweet library links to each tweet when it collects the Twitter messages. Once this action was applied, we reduced the sample to 213,567 tweets. We manually reviewed the tweets by language and identified user communities from South America, based on usernames, location, description and their social cluster, we then separated these messages to keep only the Spanish messages written in Spain. After manually checking the messages with more reach and the most active users we were able to verify its effectiveness.

The final step was filtering the top 25 messages by reach for each language. In cases where the message did not contain text, we had to check the user’s timeline to identify its meaning and origin. Starting with this partial dataset from these tweets, we searched the complete dataset (N= 213,567) for all those messages that were related to some of the main messages. We used single tweet identifier and query for retweets that contained the id of the original message. Then, we labeled the amplifying users according to whether they were promoting or debunking the unproven facts.

2. Supplementary tables

Finding 4 supplementary tables with: descriptive statistics (Table 4), and regression test (Table 5).

Table 4. Descriptive statistics. Mean, standard deviation (sd), maximum and minimum.

	Mean	SD	Max	Min
Follow official Accounts	0.47	0.5	1	0
Infected	0.78	0.41	1	0

Table 5. Logistic regression results.

<i>Dependent variable:</i>	
	Infected
Follows Official Accounts	-2.312*** (0.173)
Constant	2.747*** (0.154)
Observations	1,401
Log Likelihood	-608.257
Akaike Inf. Crit.	1,220.513
<i>Note:</i>	*p<0.1; **p<0.05; ***p<0.01