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Miscellaneous

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Enhancing Health Communication Strategies to Combat COVID-19 Infodemic Exposure: A cross-country study

Abstract

This paper explores the relationship between infodemic exposure and the reliance on different information sources during the early stages of the COVID-19 pandemic. The research aims to identify the sources that create less infodemic exposure by using data from two studies with a 10-country sample. Study 1 examines infodemic exposure by analyzing 3,723,920 COVID-19 tweets, using 5 of 25 original variables, while Study 2 analyzes reliance on COVID-19 information sources by surveying 10,000 respondents, using 9 of 111 original variables. The findings suggest that people who rely on national government information sources tend to be less exposed to the infodemic, and there is a correlation between countries with higher COVID-19 confirmed cases and people's reliance on official information sources. Likewise, people from countries with more unverified bots tweeting about COVID-19 tend to rely less on family and friends and social media as sources. Scientists and health professionals are found to be the most trusted spokespeople, rather than politicians. Finally, the research shows that 70% of the countries in the sample showed a slight reduction in their exposure risk of exposure to the infodemic within 12 months of the pandemic's start. These findings suggest significant insights for infodemic debunking efforts by government departments, public health organizations, and media industries in a context of disinformation and artificial intelligence.

Keywords

Journalism, disinformation, misinformation, AI, Trump, WHO, trust, digital platforms, vaccines, Twitter, X

1. Introduction

The COVID-19 pandemic has been accompanied by a massive infodemic. An overabundance of information, some reliable and some not, has made it extremely hard for the public to exercise their right to be informed (WHO, 2020). In such information ecosystems, citizens should have access to truthful, accurate, and reliable information to protect their health and that of others, as suggested by a study on journalistic coverage of crises (Mayo-Cubero, 2020). A critical research question at the intersection of health and risk communication is understanding how social media content evolved in the early stages of the COVID-19 pandemic, something that experts believe has not yet been sufficiently researched (Medford et al., 2020).

2. Theoretical Background

Our theoretical background is anchored in the widely used framework of Daniel C. Hallin and Paolo Mancini. The model offers a broad exploration of the conceptual foundations for the comparative analysis across countries and political-media systems globally (2011). Media frameworks are defined by the information sources operating in these ecosystems. Based on an analysis of social media posts by major news organizations in seven countries: Brazil, Chile, Germany, Mexico, Spain, the UK, and the US, a recent study examines how sources were used in the news coverage of the pandemic. The content analysis of posts published on Twitter (now X), Facebook, and Instagram suggests the dominance of public policy sources in all countries and platforms. This finding reinforces a long-standing orientation towards elites and a strong role for the state in influencing pandemic-related news. Likewise, health sources were also prominent in the news narrative (Mellado et al., 2021).

2.1. *Reliance on sources of information*

In our reliance approach, we base our analysis on the construct proposed by Wanta (1994) in the context of agenda-setting theory. This model is presented under the assumptions that if individuals perceive the media to be highly credible, they will rely on the media for information, increase their exposure to media messages, and become more susceptible to agenda-setting effects. Hence, people are often more trusting of sources they use and less so of those they do not (Toff et al., 2023). Existing literature indicates that variables linked to trust in health authorities and government institutions (e.g., national and local governments) are important correlates of citizens' compliance with public health policies, restrictions, and guidelines in the context of epidemics (Battiston, Kashyap, & Rotondi, 2021) (Blair, Morse, & Tsai, 2017). On this point, researchers have identified "the need for further scientific evidence to examine the relationship between misinformation and trust in information sources" (Stecula, Kuru, & Hall Jamieson, 2022: 2). One way to combat misinformation might be to prioritize the most trusted spokespeople. In the COVID-19 crisis, "the most credible sources are scientists, health officials, and doctors" (Nielsen et al., 2020: 16).

2.2. *Social media in crises*

Scholars have expressed "a lack of a deeper understanding of social media's fundamental role in crises" (Reuter, Stieglitz, & Imran, 2020: 4). Public health experts argue that for a self-protection message to be successful, it must reach at least 80% of the target population (Suárez, 2020). Only a combination of sources and platforms can reach that percentage. Research has shown that "reducing exposure to unverified facts is more effective in protecting the public than counteracting them" (Stecula et al., 2022: 3). Evidence suggests that having access to reliable information during crises is crucial as it saves lives and mitigates harm (Mayo-Cubero, 2021).

Consumers often consider Twitter as the primary social media platform for information (Newman et al., 2020). In a recent Pew Report, most X users say that keeping up with news is either a major or minor reason they use the platform, and about half say they regularly get news there (Shearer et al., 2024). Many of those who used Facebook for information say they come across the information incidentally. YouTube and other networks such as Instagram, Snapchat, and TikTok were valued more for entertainment and fun (Newman et al., 2023). However, things are evolving. Upon closer examination of the last Digital News Report 2024, we observe that news use across online platforms is fragmenting, with six platforms now reaching at least 10% of the respondents, compared with just two a decade ago. YouTube is used for news by almost a third (31%) of the global sample each week, WhatsApp by around a fifth (21%), while TikTok (13%) has overtaken Twitter (10%), now rebranded X, for the first time (Newman et al., 2024).

2.3. *Spreading of infodemic*

A vital factor related to the spread of disinformation is the presence of unverified bots. News media literacy interventions and fact-checkers are identified as the most effective combination to debunk it (Hameleers, 2020). Most of those who report seeing misinformation also report seeing it corrected (Bode & Vraga, 2021). Taking action against these falsehoods is particularly critical because robust research has shown that human behavior contributes more to the differential spread of falsity and truth than automated robots do (Vosoughi et al., 2018).

2.4. *Scope and study´s aims*

This article analyzes data from March 10, 2020, during the pandemic outbreak, with 118,400 confirmed cases globally (24,356 in the 10-country sample). At that time, very little was known definitively about where the virus came from, how it spread, how lethal it was, or how to combat it. This lack of clarity created a unique information environment, precisely the one we are interested in studying in this research. This study aims to contribute to the understanding of the information sources that create less infodemic. We propose that identifying these sources is an essential first step toward containing disinformation. Following the literature review and according to the aims, we posed the following research questions:

RQ1: How are infodemic exposure and reliance on different information sources correlated during the early phases of the COVID-19 pandemic?

RQ2: Is there a link between the prevalence of unverified bots—automatic Twitter accounts generally associated with spreading COVID-19 misinformation—and reliance on coronavirus information sources in the sample?

RQ3: Is the number of confirmed cases of COVID-19 in a country associated with the public's reliance on national government information sources?

RQ4: How could we redesign the information ecosystem of the 21st century to prioritize and promote truth? What role can AI play in mitigating disinformation while maintaining ethical standards in this redesigned ecosystem?

3. Methods

3.1. *Research Design*

As a brief introduction, the article is based on data from two international studies on the infodemic. Study 1, "COVID-19 Infodemics", used machine learning techniques to analyze millions of tweets and assess global exposure to the infodemic risk. The data used in the research includes a subsample of ten countries: the US, Great Britain, Canada, Brazil, France, Germany, Italy, Japan, South Africa, and South Korea. This dataset includes more than one million COVID-19 tweets recorded on March 10, 2020. The data are updated daily and published in the "COVID-19 Infodemics Observatory". Study 2, "Trust and the coronavirus," is a special survey by Edelman, a global communications company. It surveyed 10,000 people from the same sample in 10 countries about trust in sources of information on COVID-19 over the same period. Additionally, data collection was repeated exclusively for study 1 at six and 12 months (10/09/2020 and 10/03/2021) to explore possible patterns related to the risk of infodemic exposure in the countries analyzed.

The justification for the research design is that both datasets (studies 1 and 2) provide high-quality evidence captured simultaneously during a global event in progress: the COVID-19 crisis. Although more studies were developed early in the pandemic, both databases were the most comprehensive, rigorous, and reliably conducted to date. This article is presented as a first exploratory approach to a complex phenomenon with high uncertainty. Therefore, our methodological design is akin to a field experiment as it is better suited for observing and evaluating complex and unfolding interaction events. Although some control is lost (e.g., operating with secondary databases), realism increases (Kerlinger, 1986), and when realism increases, findings have greater generalizability (Keyton, 2019). Indeed, the research questions could not have been studied in a lab environment as they required reality, albeit imperfect and limited, to be tested. Quantitative, rapid data collection in the context of newly emerging infectious disease outbreaks is challenging when face-to-face contact is restricted and changes are likely to occur in short time spans (Blair et al., 2017).

3.2. *Sample*

In our sample, almost all countries show Internet penetration rates above 90%, except for Brazil (71%) and South Africa (55%) (Newman et al., 2020). In January 2020, at least 50% of internet users (aged 16-64) in all those countries used Twitter (Global Web Index, 2020). Hence, we apply the Hallin and Mancini model to examine our 10-country sample (N_3=10). According to the Hallin and Mancini media systems: six countries in our sample are representatives of the Polarized Pluralist model (Brazil, France, Italy, Japan, South Africa, and South Korea), three of the Liberal model (the US, UK, and Canada), and one of the Democratic Corporatist model (Germany) (Hallin & Mancini, 2011). The predominant model in our sample, Polarized Pluralist, is characterized by three features: indirect state control over the media, the influence of political parties on the news agenda, and a high degree of integration of the media and political elites (Hallin & Mancini, 2004). Our sample is sufficiently heterogeneous as it covers ten countries where the infodemic has a widely varying impact. Moreover, these countries fully represent the three political–media systems of the Hallin and Mancini model (2004).

3.3. *Datasets*

This article draws on high-quality datasets from two international studies on the infodemic. Study 1 is the "COVID-19 Infodemics" report in which the research team used machine learning techniques to analyze millions of tweets and filter them to assess global infodemic exposure (Gallotti, Castaldo, Valle, Sacco, & De-Domenico, 2020). The data are updated daily and published in the "Covid19 Infodemics Observatory" (https://covid19obs.fbk.eu/#/). According to these authors, data collection followed a methodology consolidated over the years. It centered on Twitter as it provides access to publicly available messages through specific requests via its application programming interface (API). A set of hashtags and keywords that have gained collective attention since the first recorded cases of COVID-19 were identified, namely: #coronavirus, #ncov, #Wuhan, #covid, #covid19, #covid-19, and #sarscov2 (De-Domenico & Sacco, 2020). The team comprises researchers from the Berkman Center for Internet

& Society at Harvard University, the Complex Multilayer Networks (Fondazione Bruno Kessler), and the University of Milan. In our research, we used original data from a subsample of study 1, "COVID-19 Infodemics", which includes ten countries: the US, UK, Canada, Brazil, France, Germany, Italy, Japan, South Africa, and South Korea. 1,497,932 COVID-19 tweets were recorded on March 10, 2020 (N_1=1,497,932). Similarly, study 2 is the special survey "Trust and the Coronavirus" conducted by Edelman, a global communications firm. It surveyed the same sample of 10 countries with 10,000 respondents (N_2=10,000). The distribution was 1,000 surveyed in each country. Study 2 noted that +/-1.0% is the 10-market global data margin of error (N_2=10,000), and +/-3.1 is the market-specific data margin of error. Furthermore, we calculated averages from combined surveys (1,000 respondents per country). This approach reduces noise and increases the signal (more observations, less chance).

3.4. *Demographic profile*

According to Edelman, the fieldwork was conducted from March 6–10, 2020. All informed public respondents met the following criteria: household income in the top quartile for their age in their country; reading or watching business/news media at least several times a week; and following public policy issues in the news at least several times a week (2020). Of the total sample (N2=10,000), 4,954 (49.4%) were males, and 5,069 (50.6%) were females. The majority of respondents were white (64.5%), followed by Hispanic or Latino (13.8%), African descent (12.3%), Asian (6.3%), Native or Indian (2.0%), and Other (1.1%). Regarding the level of education, college degree (33.2%) was most frequent, followed by secondary school (21.9%), technical school (14.1%), post-graduate degree (12.5%), some higher education (12.3%), some secondary school (4.6%) and primary school (1%). In terms of age distribution, the largest age group was over 65 (20.8%), followed by 45-54 (18.1%), 35-44 (17.5%), 25-34 (17.2%), 55-64 (16.3%), and 18-24 (10.2%).

3.5.1. Study 1 variables

The original dataset had 25 variables. However, we only selected variables that fit the research aims, and five were operationalized following the classification designed by Gallotti, Valle, Castaldo, Sacco, & De-Domenico (2020). V1 measures confirmed cases (new coronavirus cases confirmed). V2 measures COVID-19 tweets (number of tweets about coronavirus). V3 measures exposure to facts from unreliable sources, i.e., an analysis of URLs in tweets to determine whether they are trustworthy (e.g., news organizations, mainstream media, recognized scientific institutions, and news magazines) or not (e.g., fake news, hoaxes, satire, clickbait). V4 measures the number of unverified bots, that is, unverified automated accounts as opposed to verified bots that include news organizations; and, in some cases, extremely active VIP accounts. Finally, V5 measures infodemic exposure (the potential number of users exposed to reliable or unreliable URLs in tweets). Regarding measurement levels, V1-V5 are continuous, and specifically, V5 was measured with an index ranging from 0 (lowest risk of infodemic) to 1 (highest risk) with intermediate values (Gallotti, Valle, et al., 2020). Descriptive statistics of each variable are shown below (Table 1).

Table 1. Descriptive statistics variables (N_3=10)

	Minimum	Maximum	M	SD
V1 confirmed cases	7	10,149	2,435.6	3,503.5
V2 COVID-19 tweets	4,899	978,874	149,793.2	294,890.3
V4 unverified bots	1,110	405,807	61,224.9	122,686.8
V5 infodemic exposure	.01	.34	.11	.10
V6 national gov	25	63	39.7	10.9
V7 local gov	15	33	25.8	5.4
V8 int health	18	46	33.9	10.6
V10 mass media	52	73	64	6.9
V11 social media	21	72	37.5	17.5
V12 family friends	20	44	27.4	8.2
V13 daily news	50	93	70	15.8
V15 education	1	33	17	5.45

Sources: Data for variables 1-5 are from the Report "Covid-19 Infodemics" (2020) and data for variables 6-15 are from the Edelman´s Special Report "Trust and the Coronavirus" (2020). Author's elaboration.

3.5.2. Study 2 variables

The original dataset had 111 variables, of which nine variables that fit the objectives of this research were operationalized as follows. The questionnaire variables measure reliance on information sources regarding coronavirus. In the online survey, Q4 asked: "Where do you get most of your information about this virus? Please select all that apply." Seven response categories were coded as follows: V6 national government sources, V7 local government sources, V8 international health organizations sources (e.g., WHO), V9 national health organizations sources (e.g., CDC), V10 mass media, V11 social media, and V12 family and friends. V13 measured daily news consumption (percentage of daily queries for news on COVID-19). Q5 asked: "How often are you looking for and accessing information about the virus and how it is spreading? Please select one response" with a six-scale response (several times a day/ at least once a day/ every couple of days/ once a week/ less often than once a week / never). V14 measured politicization (degree of concern about the politicization of the pandemic). Q3 asked: "Please indicate your level of agreement with the statements below using a nine-point scale where one means "strongly disagree," and nine means "strongly agree". Please select one response for each". V15 measures the educational level as previously described (see demographic profile). We consider the education variable to predict user behavior concerning the infodemic. We use this variable to assess the relative media literacy of respondents as it is the best approximation we found in the survey data. Regarding the levels of measurement, V6-V15 are continuous and were coded as ordinal variables following academic convention (Stockemer, 2019). Descriptive statistics of each variable are shown below (Table 1).

3.6. *Data analysis*

We analyzed data with the statistical analysis program SPSS, version 25. According to the variables' measurement levels, the analysis strategy collected descriptive statistics: frequencies, percentages, means (M), and standard deviations (SD). Subsequently, all variables analyzed were subjected to the Shapiro-Wilk normality test (1965). This test is suitable when "fewer than 50 cases are analyzed" (Mohd-Razali & Bee-Wah, 2011: 25). The test confirmed that none of the variables had a normal distribution, so we applied Spearman's rho instead of Pearson's r to calculate bivariate correlations.

A fundamental issue in the experimental design was whether the cross-national sample (N_3=10) was sufficient to assess the existence of significant correlations. Although a larger sample would yield more representative and robust findings, the literature review suggested that the full distribution of Spearman's rho is suited for small samples (up to n = 7) and approximations for moderate sample sizes (n < 50) (May & Looney, 2020). Hence, we have created several correlation matrices to address our research questions. Table 2 shows the correlations between study 2 variables.

Table 2. Correlation Matrix Spearman's rho (N_2=10,000)

		V6	V7	V8	V10	V11	V12	V13	V15
V6 national gov	Sig. (2-tailed)	.	.	.	.	.	.	.	.
	Correlation								
V7 local gov	.	.595	.	.	.	.	.	.	.
	.	.070							
V8 int health	.	.030	.480	.	.	.	.	.	.
	.	.934	.160						
V10 mass media	.	-.073	-.074	-.691*	.	.	.	.	.
	.	.841	.839	.027					
V11 social media	.	.152	.665*	.183	.434	.	.	.	.
	.	.675	.036	.613	.210				
V12 family friends	.	.012	.327	-.235	.580	.804**	.	.	.
	.	.973	.356	.513	.079	.005			
V13 daily news	.	.707*	.636*	-.052	.285	.526	.212	.	.
	.	.022	.048	.887	.424	.118	.557		
V15 education	.	.562	.775**	.149	-.047	.338	.335	.379	.
	.	.091	.008	.682	.898	.340	.343	.280	

Note: * $p < .05$ ** $p < .01$

Source: Data for variables 6-15 are from the Edelman´s Special Report "Trust and the Coronavirus" (2020). Author's elaboration.

Likewise, Table 3 shows the correlations when crossing study 1 and study 2 variables.

Table 3. Correlation Matrix Spearman's rho (N_3=10)

		V6 nat gov	V7 local gov	V8 int health	V10 mass media	V11 social media	V12 family friends	V13 daily news
V1 confirmed cases	Correlation	.636*	.178	-.347	-.030	-.316	-.250	.402
	Sig. (2-tailed)	.048	.623	.327	.933	.374	.486	.249
V2 COVID-19 tweets	.	-.418	-.632*	.164	-.543	-.766**	-.799**	-.451
	.	.229	.050	.650	.105	.010	.006	.191
V4 unverified bots	.	-.333	-.620	.061	-.549	-.839**	-.872**	-.402
	.	.347	.056	.868	.100	.002	.001	.249
V5 infodemic exposure	.	-.648*	-.325	-.182	.024	-.377	-.287	-.482
	.	.043	.359	.614	.947	.283	.422	.159

Note: * $p < .05$ ** $p < .01$

Sources: Data for variables 1-5 are from the Report "Covid-19 Infodemics" (2020) and data for variables 6-13 are from the Edelman´s Special Report "Trust and the Coronavirus" (2020). Author's elaboration.

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Additionally, Table 4 shows the Infodemic Exposure trend data.

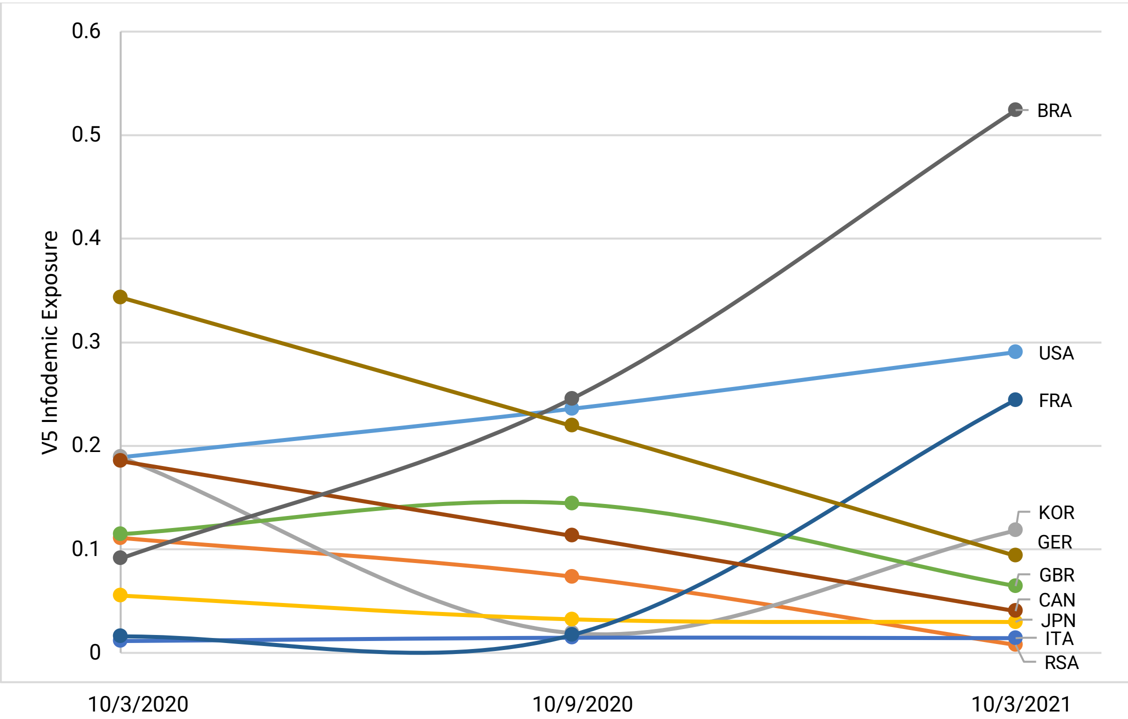
Table 4. Infodemic Exposure Trend (V5)

Date	USA	RSA	KOR	JPN	ITA	GBR	FRA	CAN	BRA	GER
10/3/2020	0.1889	0.111	0.1891	0.0553	0.0114	0.1146	0.0159	0.1852	0.0911	0.3433
10/9/2020	0.2357	0.0736	0.0191	0.0324	0.0146	0.1443	0.0172	0.113	0.2454	0.2192
10/3/2021	0.2904	0.0077	0.1181	0.0298	0.0142	0.0645	0.2443	0.0403	0.5239	0.0937

Source: Data for variable 5 is from Covid-19 Infodemics Observatory (2022). Author's elaboration.

Finally, Figure 1 is the graphical representation of these measurements at three different time points.

Figure 1. Infodemic Exposure Trend



Source: Data for variable 5 are from the Report "Covid-19 Infodemics" (2020). Author's elaboration.

We followed two strategies to address the problem of multiple comparisons and minimize an inflated Type I error rate due to multiple statistical comparisons. First, we eliminated non-priority variables to focus the analysis on significant correlations and reduce the number of comparisons as much as possible. In this regard, and after thorough research: V3 was removed from study 1, and V9 and V14 from study 2. Second, we also followed the recommendation of the American Psychological Association to accurately report p-values instead of simply reporting "p < .05" so that readers who require a different level of inference can apply an alternative approach and/or corrections if deemed necessary. Consequently, all comparisons have been recalculated, including p-values in all tables (Tables 2, 3, and 4). These strategies follow the line recommended by some experts (Frane, 2015). Specifically, Rothman defends that not adjusting for multiple comparisons is preferable because it will lead to fewer interpretation errors when the data under evaluation are not random numbers but actual observations of nature. Furthermore, scientists should not be so reluctant to explore leads that may be wrong that they penalize themselves by missing possibly significant findings (1990).

4. Findings

Finding 1: *More education correlates with reliance on local government information sources (1a). Likewise, daily consumption of COVID-19 information correlates with reliance on both national and local government information sources on coronavirus (1b)*

We find that the more education people have, the more they tend to rely on local government information sources (1a). Findings suggest a robust association between V15 and V7 (rho=.775, p<.01). We also observe that people who consume daily COVID-19 information tend to rely on local and national government information sources (Table 2). Findings suggest a correlation of moderate intensity between V13 and V6 (rho=.707, p<.05) and a link between V13 and V7 (rho=.636, p<.05).

Finding 2: *Reliance on social media information sources on coronavirus correlates with reliance on both local government and family and friends as information sources on COVID-19*

We find that people who tend to rely on social media as an information source on COVID-19 also tend to rely on both local government and family and friends as coronavirus information sources (Table 2). Results suggest a robust correlation between V11 and V12 (rho=.804, p<.01). The correlation matrix also suggests an association of medium intensity between V11 and V7 (rho=.665, p<.05).

Finding 3: *Reliance on mass media information sources on coronavirus negatively correlates with reliance on international health organization COVID-19 information sources*

Our outcomes suggest that people who rely on news outlets tend to rely less on the WHO as a coronavirus information source (Table 2). Findings suggest a negative correlation of moderate intensity between V10 and V8 (rho=-.691, p<.05).

Finding 4: *Infodemic exposure negatively correlates with reliance on national government information sources on COVID-19 (4a). Moreover, the number of confirmed COVID-19 cases confirmed correlates with reliance on national government information sources (4b).*

We find that people who rely on national government information sources about COVID-19 tend to be less exposed to the infodemic (Table 3). Likewise, our findings suggest an association between people from countries with a higher number of confirmed cases of COVID-19, affected by the pandemic, and people's reliance on national government information sources (Table 3). These outcomes come from crossing variables of studies 1 and 2. The inferential analysis yields several significant correlations like a negative link between V6 and V5 (rho=-.648, p<.05) and an association of medium intensity between V6 and V1 (rho=.636, p<.05).

Finding 5: *The number of COVID-19 tweets negatively correlates with reliance on family and friends, social media, and local government as information sources on coronavirus*

Our model suggests that people from countries with more COVID-19 tweets tend to rely less on family and friends, social media, and local government as information sources about coronavirus (Table 3). The outcomes suggest a robust negative correlation between V2 and V12 (rho=-.799, p<.01), as well as V2 and V11 (rho=-.766, p<.01). Findings also suggest a moderate negative correlation between V2 and V7 (rho= -.632, p<.05).

Finding 6: *The number of unverified bots negatively correlates with reliance on family and friends and social media as information sources on coronavirus*

We observe that people from countries with more unverified bots tweeting about COVID-19 tend to rely less on family and friends and social media as information sources about coronavirus (Table 3). Findings suggest a robust negative correlation between V4 and V12 (rho=-.872, p<.01) as well as V4 and V11 (rho=-.839, p<.01).

Finding 7: *70% of the sample´s countries slightly reduced their risk of exposure to the infodemic within 12 months of the pandemic's start.*

We observed V5, which collects the infodemic risk index to determine the countries' infodemic exposure. Precisely, V5 was measured with an index ranging from 0 (lowest risk of infodemic) to 1 (highest risk) with intermediate values (Gallotti, Valle, et al., 2020). After collecting data from 10 March 2020, the research team decided to repeat the data collection at six months and twelve months to explore possible trends in the sample of 10 countries analyzed (Figure 1). 3,723,920 tweets were captured via API (N1=1,497,932 from 10/03/2020 plus N3=2,225,988 from 10/09/2020 and 10/03/2021). We found that 70% of the countries in the sample: South Korea, Germany, Great Britain, Canada, Japan, Italy, and the Republic of South Africa, slightly reduced their risk of infodemic to a low risk of around 0.1. Conversely, Brazil had the highest risk scaling from 0.1 on 10/03/20 to above 0.5 on 10/03/21. The USA ranked second, with a medium-low risk exposure (0.3) and a consistent time trend. France was the third country with medium-low risk, although with a significant rise over six months (10/09/2020-10/03/2021). The data also suggest that the sharpest decline from moderate risk (0.4) to low risk (0.1) was in the case of Germany. For more information on the data matrix exploring the evolution of V5 in the period 10/03/2020-10/03/2021, please see Table 4.

5. Discussion

5.1. *Government sources against infodemic*

This research provides evidence from an exploration of reliance on different information sources and infodemic exposure. We found that people who rely on national government information sources about COVID-19 tend to be less exposed to the infodemic (Finding 4a). However, it's crucial to interpret this finding cautiously. The observed negative correlation between reliance on government sources and infodemic exposure doesn't necessarily imply a causal relationship. Several alternative explanations could account for this association.

First, media literacy: people with higher media literacy skills might be more likely to rely on official government sources while being less susceptible to misinformation, without one directly causing the other. Second, trust in institutions: general trust in government institutions could lead to both higher reliance on official sources and lower susceptibility to misinformation from unofficial sources. Third, information-seeking behavior: people who actively seek out information from official sources might also be more discerning about the information they encounter overall. Fourth, government communication effectiveness: countries with more effective government communication strategies might foster both higher reliance on official sources and lower infodemic exposure.

5.2. *Media systems and the rally 'round the flag effect*

When categorizing the sample of 10 countries by their media systems, we can further interpret the findings. Our model suggests that people from countries with more COVID-19 tweets tend to rely less on family and friends, social media, and local government as information sources (Finding 5). As mentioned, the predominant model in our sample, Polarized Pluralist, is characterized by three features: indirect state control over the media, political influence on the news agenda, and a high degree of integration of media and political elites (Hallin & Mancini, 2004). Thus, we deduce that the dominance of organized pluralism (typical of the polarized model) versus individual liberalism (typical of the liberal model) could explain the low reliance on these sources. This evidence may be valuable in designing more precise strategies and policies to combat the infodemic in these specific political-media ecosystems. Proposals could include raising the standard of media literacy in general and specific social sectors, strengthening the regulatory framework to protect quality information, or working with digital platforms to debunk mis/disinformation.

Furthermore, we found that daily consumption of COVID-19 information is associated with reliance on both the national and local government as information sources (Finding 1b). Considering that the analysis was conducted at the beginning of the pandemic (March 10, 2020), we could deduce that the public's perception of the pandemic impacting their country was associated with reliance on the national government. This evidence could help understand the link between world political leaders appealing to national unity and the increase in COVID-19 confirmed cases (e.g., President Moon in South Korea and Prime Minister Conte in Italy). This finding aligns with the rally 'round the flag effect suggesting that citizens tend to support their national leaders in times of international crises.

5.3. *More scientists, fewer politicians*

This research also explores other factors related to trust in public policy sources of information in times of crisis. We observed an association between people from countries with a higher number of confirmed COVID-19 cases and their reliance on government information sources (Finding 4b). This finding aligns with Mellado et al.'s (2021) study across platforms in seven countries, which found a predominance of public policy sources in the pandemic's journalistic narrative. The evidence thus suggests a reinforcement of the strong role of the state and political-media elites in influencing news about the pandemic (2021).

Nevertheless, we note that "85% of respondents stated they needed to hear more from scientists and less from politicians" (Edelman, 2020: 5). This significant contradiction highlights a practical application for policymakers. For citizens, the most credible spokespersons during an infodemic are scientists and health professionals, not politicians. This finding is consistent with recent research that has approached the phenomenon from various methodological angles (Nielsen et al., 2020). Fear and anger alter social media users' behavior. Consequently, when people feel their lives might be in danger, they tend to refrain from retweeting about irrelevant matters as they know where to find more rigorous and reliable information sources.

5.4. *Reliance on close versus distant sources*

We observe significant insights when examining findings based on proximity to information sources. We found that reliance on social media platforms (such as Twitter, Facebook, LinkedIn, Instagram, YouTube, TikTok, WhatsApp, or WeChat) is associated with trust in local government and family and friends for information (Finding 2). Both share a closeness link, indicating that people tend to rely on COVID-19 information sources with emotional or locational bonds. These findings suggest a clear strategy for public health authorities to reinforce messages through sources that align with this closeness. An example is implementing offline and online communication channels involving municipalities, local health centers, and community radio.

Regarding distant sources, international health organizations are the most remote for citizens. We found that people who rely on mass media tend to rely less on the WHO (Finding 3). Notably, one of President Trump's first measures upon returning to the White House was the withdrawal of the US from the WHO. This decision's impact on world health policy and US public health remains to be seen, as the WHO's main shareholder abruptly withdraws its political, technical, and economic support (Stolberg, 2025). We propose more respectful and closer

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cooperation between governments and international health institutions. Given their extreme visibility and impact, these main actors' messages should be consistent and focused solely on safeguarding public health. This could be achieved by enhancing health and media literacy and debunking health misinformation using credible sources.

5.5. *Unverified bots and early identification*

Unverified bots play a key role in amplifying disinformation, often enhanced by AI and LLMs. This research aims to address the gap in studies documenting real-time monitoring of COVID-19 data from social media. We found that people from countries with more unverified bots tweeting about COVID-19 tend to rely less on family, friends, and social media for information (Finding 6). This association may be explained by the proliferation of dis/misinformation through unverified bots on social platforms. The infodemic can employ sophisticated tactics, making it challenging to distinguish accurate information from falsehoods. Consequently, people may turn away from personal connections and social media, potentially exposing themselves to more misinformation.

Early identification and intervention are crucial in containing the infodemic's spread. Prompt action can prevent misinformation dissemination through inner circles, encouraging reliance on accurate information from trusted contacts. This approach should be combined with proven measures like media literacy and fact-checking. Research indicates that misinformation debunking often lacks coordination among key players such as governments, social media platforms, and fact-checkers. The hydroxychloroquine case exemplifies how discoordination can have devastating health effects. Moreover, vaccine misinformation has become a major concern, potentially undermining public trust and leading to hesitancy.

While social media contributes to the infodemic, it can also be part of the solution. Our analysis highlights the need for improved cooperation between government sources and social media platforms. Could AI, LLMs, and algorithms be enhanced to better tag and debunk disinformation? Evidence suggests that increased human supervision in knowledge curation could help tackle the infodemic by identifying false information, promoting credible sources, and educating the public about vaccine importance.

5.6. *Reduced risk of infodemic*

The data suggest a slight trend toward reducing infodemic risk exposure in the sample (Finding 7). Seventy percent of countries decreased their exposure risk within 12 months of the pandemic's onset. In our analysis of the year-long evolution, the most worrying case was Brazil, which moved from a slight risk to a moderate risk by the end of the period. The US ranked second, with a medium-low risk (0.3) and a constant time trend. France also showed a medium-low risk, with a significant rise over six months (10/09/2020-10/03/2021). Germany exhibited the sharpest decline, dropping from moderate risk (0.4) to low risk (0.1). We infer that various factors, including the different media systems of the sample countries (Hallin & Mancini, 2011), could explain these observed trends. These findings raise relevant research questions about causal relationships for future investigation.

6. Limitations

While this research builds on previous studies, it aims to provide new insights by analyzing data from multiple countries during the early stages of the COVID-19 pandemic. We note some caveats for the research presented in this paper. The analysis is based on a limited sample across ten countries, which may affect generalizability. Future research could replicate the study with larger samples to increase representativeness. Correlation analysis only depicts whether two

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variables are related and how closely they follow a positive or negative direction. Therefore, correlation does not necessarily equal causation. Although the data collection covers twelve months (10/03/2020-10/03/2021), which is sufficient for an exploratory approximation, further longitudinal research is needed to explore patterns and trends throughout the pandemic.

We also note some data limitations and possible selection biases in study 1. While the gathering and integration of vast sources of user-generated data allows us to analyze complex collective phenomena in near real-time, this approach is subject to limitations inherent in user-generated content and data selection biases. All Twitter-based research must contend with the intrinsic demographic limitations of Twitter's penetration: findings apply primarily to well-educated males between the ages of 25 and 65 (65% of Twitter users) (Gallotti et al., 2020). Despite these limitations, we believe this piece contributes to establishing a robust research agenda for studying infodemics. Future research should expand this evidence by analyzing different demographics across data sources and social media platforms.

Study 2 also has limitations. Online surveys introduce bias regarding who was approached to take part. While the respondents were broadly representative of the general population on several basic demographic features, we cannot conclude that they were fully representative. Another limitation concerns the accuracy of the questions that measure study 2 variables. This paper relied on a limited measure of reliance on information sources using secondary data. Trust is a construct with many nuances, especially when considering the critical distinction between news media, social media, and government information sources. Finally, the study's exploratory nature leads to many conclusions, increasing the possibility that an identified correlation is due to chance (due to multiple comparisons). We have tried to minimize this potential error with the methodological strategies explained above (see Data Analysis). Future research could explore and deepen these findings, specifically with more sophisticated and multifactorial analyses.

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