Patterns of COVID-19 Communication Among Americans: Analyzing Local Vulnerabilities, Polarization, and Political Dynamics

Wenyou Ye[1]* and Liviu Aron[2]

[1] Philip Merrill College of Journalism, University of Maryland, 7765 Alumni Dr, College Park, MD 20742

[2] Harvard Medical School, 77 Avenue Louis Pasteur, Boston, MA 02115

* Correspondence should be addressed to W.Y. wenye@umd.edu

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ABSTRACT

The communication among citizens during public health crises is poorly understood, yet it may be crucial for understanding the origins of non-compliance with public health guidelines, the emergence of mass polarization, and the effectiveness of crisis management efforts. To gain insight into the communication networks among regular Americans during the COVID-19 pandemic, our study monitored COVID-19 discourse on Twitter over the first three years of the pandemic. We scrutinized 4.5 million geotagged and randomly sampled tweets from 786,414 users across the United States. Our findings reveal that local political leanings and socioeconomic factors strongly influenced the patterns of COVID-19 communication among citizens. We identified local vulnerabilities, such as the preferential use of politicized, conspiratorial, and religious language, which were predictive of higher COVID-19 mortality in corresponding communities, as well as patterns of communication resilience, particularly in liberal communities. Additionally, we uncovered polarized communication patterns that distinctly characterized liberal and conservative communities. Furthermore, our analysis demonstrates that citizens' COVID-19 communication was less politicized compared to that of the news media, and we found that Democratic politicians who continued to focus on COVID-19 in late 2022 were more likely to lose their election bids. Our study deepens the understanding of citizens' pandemic attitudes, uncovers local vulnerabilities and resilience patterns, and suggests a role for social media communication networks in predicting public health and electoral outcomes.

INTRODUCTION

The COVID-19 pandemic represents an unprecedented public health challenge, which affected the lives of billions of people worldwide, reshaping global economies, altering social dynamics, and exposing deep-seated inequalities in healthcare systems. The pandemic has been profoundly shaped by local vulnerabilities and polarization, as well as by ideological conflicts, which exacerbated public health disparities, fueled misinformation, and hindered unified responses to the crisis.

A significant obstacle to effective management efforts has been the pervasive COVID-19 polarization, which has been especially pronounced in the United States. This deep-seated division has not only undermined public health initiatives but eroded trust in institutions, and hindered the collective action necessary to combat the pandemic effectively (Smith et al., 2023; van der Linden, 2022) Social media networks may have contributed to the crisis by amplifying misinformation about the pandemic (Ajekwe, 2022) but also by fostering partisan divisions between Democrats and Republicans around COVID-19 related issues (Hart et al., 2020; Jiang et al., 2021; Lang et al., 2021).

The growing rift among Americans on specific issues, divided along partisan lines, is commonly known as polarization or mass polarization. Political scientists distinguish between two primary forms of polarization: ideological polarization and affective polarization. The former is characterized by differences in political belief systems, while the latter involves animosity toward opposing groups. Fiorina and Abrams (2008) have examined various theoretical and practical approaches to mass polarization, proposing that it should be seen as a process. This process evolves from a unimodal distribution of public attitudes, beliefs, or behaviors related to a particular issue to a bimodal—or even multimodal—distribution. In such distributions, individuals' varying political ideologies lead to divergent attitudes, beliefs, or behaviors concerning matters of public interest.

The nature of mass polarization has ignited a vigorous debate within the field. Researchers such as Morris Fiorina have posited that the level of mass ideological polarization in the U.S. is negligible, though they acknowledge the presence of elite polarization (Fiorina & Abrams, 2008). Conversely, other scholars, including Abramowitz and Saunders (2008), contend that mass polarization does indeed exist in the U.S. More recent evidence provided by Abramowitz (2022) supports the notion that the American public has experienced heightened polarization in recent years. Abramowitz utilizes national election survey data spanning from 1972 to 2020 to illustrate that the correlation between party identification and five major issues, as well as the correlation between ideological identification and the same issues, has steadily intensified during this period. Furthermore, Abramowitz presents evidence indicating that the most politically-engaged Democrats or Republicans hold even more polarized stances on key policy issues. This underscores the idea that the level of political interest and participation closely correlates with polarization among the general public. The main drivers of partisan sorting and mass polarization remain poorly understood.

Political polarization of COVID-19-related beliefs, attitudes and behaviors has been extensively documented in Democratic- and Republican-predominant areas in the U.S. during the COVID-19 pandemic. Numerous studies have documented stark divisions between Democrats and Republicans, across different geographical areas and demographics (Beleche et al., 2021) which may explain the different health outcomes in regions that are predominantly liberal or conservative. The politicization and polarization of the current COVID-19 pandemic has been suggested to have far-reaching societal consequences, including higher death rates among Republicans who refuse to adopt preventative behaviors – such as mask-wearing, social distancing, or vaccination against the coronavirus (Owens, 2022).

SOCIAL NETWORKS AND COVID-19 CRISIS MANAGEMENT

The causes for this marked politicization and polarization in public attitudes, beliefs, and behaviors toward COVID-19 are currently unclear. One major driver of ideological polarization are the political elites, which can propagate partisan health information (Kerr et al., 2021). A second major culprit for the polarization of COVID-19 has been suggested to be the media. Partisan media coverage of COVID-19 may have played a role in polarizing mass beliefs, attitudes, and behaviors toward COVID-19 (Hart et al., 2020).

A third major culprit that drives mass polarization may be one's peers and social networks (Ajekwe et al., 2022). Thus, social networks, including social media, may provide a space where people with similar views interact, and strengthen their attitudes and beliefs. It has proposed that social networks may directly contribute to mass polarization of COVID-19 attitudes, beliefs and behaviors (Wang et al., 2022). Moreover, it was estimated that approximately one third of Americans were exposed to misinformation about COVID-19 through their own social networks (Nielsen et al., 2020) In the early stages of the pandemic, the reluctance of the Center for Disease Control (CDC) to release COVID-19-related information before it was fully confirmed scientifically and clinically (Cheng et al., 2021) may have facilitated the spread of misinformation online, given the uncertainty of the situation. The interplay between social media communication and pandemic management efforts are an integral part of the emerging field of *social informatics*, which aims to better understand how communication systems, as well as social and cultural systems, norms and values (such as trust in information, the effects of social identity and stratification, or inequality) interact during different societal contexts (Antonucci et al., 2017; Sawyer & Howard Rosenbaum, 2000). Our computational analysis of COVID-19 communication among ordinary Americans throughout the pandemic advances this emerging field and offers a valuable bioinformatic resource for further exploration into the role of citizen communication during public health crises.

This study aims to better understand the impact of social media networks, as well as political ideology and socioeconomic factors on the emergence of partisan sorting and mass polarization during the COVID-19 pandemic. It also aims to uncover patterns of COVID-19 communication that conferred local vulnerability during the pandemic, as well as identify communication patterns that likely conferred local resilience.

Our research is conducted on the social media platform Twitter, a major hub for online communication. Over 60 million Americans had a Twitter account in 2021, and over 70% of them were getting their health information from Twitter (Mitchell & Liedke, 2021). Moreover, 36% Democrats, 21% Republicans and 29% independents were active on Twitter in 2019 (Pew Research Center, 2019), making it a suitable platform for health and political communication research at the national level (Funk & Gramlich, 2021).

In our study, political ideology is a key variable, as mounting research has shown that political ideology is a strong indicator of predicting attitudes toward COVID-19 and its preventative measures (Kerr et al., 2021; Rothgerber et al., 2020). Indeed, previous research has suggested an inverse correlation between political conservatism and health beliefs toward COVID-19 and preventative measures (Rothgerber et al., 2020).

Another set of key variables in our study are socioeconomic circumstances across U.S. communities. Paul et al. (2021) has cautioned that, in addition to ideology, socio-economic factors may also influence the attitudes and beliefs toward COVID-19, both at the individual and population levels.

Our paper aims to advance our understanding of social media's contribution to mass polarization and its ability to mirror citizens' attitudes and beliefs by leveraging the power of computational methods to survey millions of social media posts by ordinary Americans on Twitter, during the first three years of the pandemic (between January 2020 and December 2022). In addition, our analytical approach features a longitudinal design, which may be best suited to uncover patterns of partisan divisions and mass polarization, which tend to develop over time (Van Aelst et al., 2017), and attitude changes. Our study of Twitter posts further analyzed the real-world spontaneous communication and online behavior of a large population sample that was geo-located in thousands of U.S. cities and counties, combined with the detailed analysis of local ideological and socioeconomic features of cities and counties.

Because it has been found that mass polarization patterns and partisan sorting are closely related to political ideology, we first explored a potential relationship between political ideology and COVID-19 communication online. We collected over 4.5 million geotagged and randomly sampled tweets from 786,414 users across the United States, and analyzed the pool of tweets posted by all users residing in every city and county. We then accessed the ideological scores of individual cities and counties to determine whether the ideology of a community may predict the overall pattern of COVID-19 Twitter communication by its residents, taken in aggregate. We thus ask the first research question (RQ):

RQ1: ***Does the overall political ideology of users' local communities predict their topic usage and sentiment of COVID-19 communication on Twitter?***

It is currently unclear which, if any, factors other than ideology may influence the processes of partisan sorting or mass polarization.Gidron et al. (2020) provided evidence that, in addition to political affiliation, religiosity, beliefs in conspiracy theories, and the level of education may also influence COVID-related beliefs. For example lower education levels correlate with an increased level of COVID-19 vaccine hesitancy and rejection (Haakonsen & Furnham, 2022). To further explore a role for socioeconomic factors in the emergence of partisan divisions during the COVID-19 pandemic, we ask our second RQ:

RQ2: ***What, if any, socio-economic aspects of users' local communities predict their topic usage and sentiment of COVID-19 communication on Twitter?***

SOCIAL MEDIA NETWORKS, LOCAL VULNERABILITIES AND RESILIENCE

In 2023, roughly half of U.S. adults obtained their news through social media (Pew Research Center, 2023). Over 60 million Americans had a Twitter account in 2021, and over 70% of them were getting their health information from Twitter (Mitchell & Liedke, 2021). Social media may not only be a major source of news published by news media, but it also facilitates the shaping of news by a user's own online social network – which may share specific news, comment on others, or create original posts that include news coverage by the news media combined with personal comments by the post creator. Guess et al., (2023) recruited 193,880 Facebook users and blocked half of the respondents from seeing reshared content from their social networks. They found that the removal of reshared posts significantly decreased the political information, including misinformation, that the users were seeing. This in turn led to fewer overall clicks and reactions by these users on Facebook, and to a decrease in users' knowledge of current political events. These observations suggest that the social media networks of individual users may play a major role in shaping their knowledge about recent facts -- and could influence their attitudes, beliefs and behaviors.

A 2014 Pew research poll found that nearly two-thirds (63%) of consistent conservatives and about half (49%) of consistent liberals say most of their close friends share their political views. Besides people preferring to congregate with others online, based on their personal connections as well as shared ideology or interests, the segmentation of the news media can further contribute to the emergence of online "bubbles" in which entire groups of people consume the same type of information. This can lead to the emergence of echo chambers, which may strengthen partisanship, drive mass polarization and contribute to attitude change.

It remains unclear what effect, if any, does the online association and clustering of like-minded peers have on the emergence and spread of messages about the pandemic, and how these may contribute to local vulnerabilities during the pandemic. We asked whether the patterns of COVID-19 communication that are characteristic of users residing in the same community can predict local vulnerability or resilience to the coronavirus and the associated COVID-19 disease.

RQ3: ***Does the dissemination of COVID-19 news through social media by local community members predict local vulnerabilities or resilience to COVID-19 in American communities?***

INFLUENCE OF NEWS MEDIA AND POLITICAL ELITES ON COVID-19 COMMUNICATION

The contribution of news media to partisan sorting and mass polarization is currently poorly understood. Available evidence suggests that media may influence not only people's knowledge of events, but may also engage them politically. A study conducted by Prior (2005) has suggested that, in the high-choice modem media environment, giving people the choice in selecting their media content may increase their political engagement and turnout. Prior's survey of 2,358 U.S. residents found that increasing content preference and media choice also increased their ability to predict people's political knowledge and political engagement (voting and turnout during elections.

Because of the media's political bias and segmentation along ideological lines, some have suggested that exposure to pro-attitudinal content – news that is covered with a liberal, or conservative, bias – may reinforce people's beliefs and may accelerate divisions. If so, it has been proposed that exposure to counter-attitudinal content may reduce partisan divisions. A study by Guess et al. (2021) conducted a randomized longitudinal experiment in which they asked people to change their media consumption patterns – by changing their default browser settings and social media following patterns from receiving news from liberal media to receiving news from conservative media, and vice versa. This change was implemented for a period of at least 8 weeks. This intervention did not alter people's opinions or affect, suggesting that exposure to counter-attitudinal content, at least for this short period of time, may not change ideological or affective polarization patterns. But this intervention did decrease people's trust in the mainstream media (up to one year after the experiment), suggesting that exposure to counter-attitudinal content may decrease people's trust in the media and the media content they consume. Thus, the contribution of the media to mass polarization and partisan divisions remains unclear.

To further explore a potential role for the media in driving partisan divisions and polarization, we asked whether the degree of politicized coverage of COVID-19 by the news media was associated with a similar degree of COVID-19 politicization in the Twitter posts of ordinary citizens. We thus are asking:

RQ4: *How similar are the degrees of politicization of COVID-19 communication on Twitter by the general public compared to mainstream U.S. media?*

According to the democratic theory proposed by Berelson (1952), the vitality of a democratic system requires its citizens to be actively engaged in political discourse, such as voting in elections and participating in political discussions. Polarization may generate a higher voter turnout during a presidential election and mobilizes voters to discuss more about politics (Abramowitz & Saunders, 2008), albeit this might be a short-term effect. Furthermore, polarization can incentivize political parties and prominent politicians to offer clearer policy packages to appeal to their issue publics, so it may become easier for voters to form policy attitudes and preferences for candidates and political parties.

Remarkably, the interaction between political elites and voters may be bidirectional – with voters having the ability to shape the actions of their elected political

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representatives. For example, a study by Napier and Luguri (2016) suggested that voters can exert electoral pressure and may exert a moderating role on politicians. The study found that voters can decrease ideological polarization among U.S. congress members, further highlighting the intimate connection between politicians and their constituents.

Effective communication on social media platforms like Twitter has become a major avenue for candidates to engage and mobilize voters (Wike et al., 2022; Young Mie Kim, 2009) and can help enhance politicians' media presence and public profile (Grover et al., 2019). The engagement of potential voters is crucial for candidates to run successful election campaigns. However, engaging potential voters can be challenging due to their diverse attitudes and beliefs. In elections, McKelvey et al. (2014) and Jungherr (2016) argue that messages and audience metrics generated by the Twitter public are valuable in indicating a candidate's performance and strength and public opinion during an election. Studies have found consistency between online and offline political communication for political candidates and non-political elites (McKelvey et al., 2014; Tumasjan et al., 2010). In addition, Ceron et al. (2014) argue that as access to digital communication increases among the general public, the accuracy of social media analytics in capturing public opinion improves.

Social media is a helpful platform for studying public opinion, including voter opinion, because it allows researchers to observe non-self-report attitudes and behaviors either individually or in aggregate at low costs, compared to traditional public opinion surveys (Gayo-Avello et al., 2023). In recent years, there has been an influx of research that explored the potential of using social media analysis to predict the effectiveness of political communication and the performance of candidates during elections. To achieve this goal, various social media audience engagement metrics have been analyzed, including likes, retweets, mentions, hashtags, and sentiments, as indicators to forecast the outcomes of elections (Gaurav et al., 2013; Sabuncu et al., 2020; Singh & Shukla, 2021; Vepsäläinen et al., 2017). Although some efforts to predict elections or survey public opinion using social media data have shown success, it's important to note that these endeavors alone are insufficient for understanding the connection between social media signals and public opinion. The nature and stability of this relationship still require further exploration and investigation (Gayo-Avello et al., 2023).

Our study further explores the possibility that social media platforms may not only provide insights into the attitudes of everyday Americans, including attitudes toward COVID-19, but may also offer glimpses into voter opinions and intentions during election seasons. Investigating the connection between political elites and ordinary citizens on

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social media, our study aims to explore whether and how these groups communicate online about COVID-19, and what such interactions may reveal about citizens' attitudes towards the COVID-19 pandemic and the way in which politicians contribute to its management.

To begin exploring the attitudes of potential voters toward political elites during a later stage of the COVID-19 pandemic, and their assessment of elites' communication and leadership skills, we examined the COVID-19 communication of by candidates vying for seats in the U.S. House of Representatives during the 2022 midterm elections, a period when COVID-19 remained a pertinent topic in political discussions. Comprehensive data regarding the Twitter activity of political candidates, including their party affiliations and all tweets posted in the two months preceding the midterm elections, was collected. The objective was to assess the efficacy of their COVID-19 communication strategies and determine whether adeptness in addressing COVID-19 concerns might have bolstered their electoral prospects. Consequently, the study sought to answer the following question:

RQ5: Can the effectiveness of politicians in engaging Twitter audiences with their COVID-19 communication predict their chances of winning elections?

DATA AND METHODS

Experimental Design

The review of studies of polarization by Van Aelst et al. (2017) concluded that "[it was] striking that none of these studies [was] based on a longitudinal design. Because polarizing issues become polarizing over time, we believe it is critical to evaluate the temporal evolution of communication about these issues, to determine whether a pattern of polarization, or partisan sorting, develops over time. This study of COVID-19 as a polarizing issue covers a three-year period between January 2020, when the first infections with coronavirus were reported, and December 31, 2022.

Political ideology scores and socio-economic characteristics of U.S. communities

Using the American Ideological Project (Warshaw & Tausanovitch, 2022), we retrieved political ideology (mrsp) scores for U.S. cities and counties, based on their citizens' voting records in presidential, congressional, and state-level elections from 2006 to 2021. The ideology score of a city or county, named mrp score, is a value between -1

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and +1. A positive mrp value close to 1 indicates higher conservative ideology, a negative value close to -1 indicates a higher liberal ideology, while values around 0 indicate an ideologically-neutral city or county.

The American Communities Project at Michigan State University (American Communities Project, 2022) defined 15 major types of American communities, with each city in the U.S. belonging to one of these 15 categories. In addition to community types, detailed socioeconomic data was obtained for over all cities and counties studied in this paper. Median household income, percentage of the population holding a bachelor's or higher degree, employment rate, and public health insurance coverage rate were obtained from the U.S. Bureau of Economic Analysis. COVID-19-related data (daily numbers of infections/cases, COVID-19 deaths, COVID-19 vaccination rates) was obtained from the Centers for Disease Control and Prevention and New York Times databases. Unemployment data was from the U.S. Census Bureau.

Tweet retrieval

To automatically retrieve COVID-19-related tweets from U.S. cities and counties, we used a list of keywords identified by previous research (Ye et al., 2021) which we have expanded. We then used Python's requests package and Twitter API for Academic Research to retrieve COVID-19-related tweets that were posted by geo-located members of the communities between January 1, 2020, and December 31, 2022. As a result 4,505,399 Twitter posts by users geolocated in 11,630 U.S. cities and 2,380 counties were collected (Table 1). Taken in aggregate, these U.S. communities which are home to over 250 million people. Table 1 shows the median, medium and minimum numbers, as well as the 75% and 25% percentiles, of tweets retrieved from the U.S. cities and counties.

Table 1. Summary of COVID-19-related tweets analyzed in this study

		COVID-19-related tweet number				
No. of cities with tweets		**Median**	**Maximum**	**75% Percentile**	**25% Percentile**	**Minimum**
	all, n=11,630 cities	34	216,805	129	9	1
	≥100 tweets, n=3,123 cities	325	216,805	831	163	100
	≥500 tweets, n=1,216 cities	1124	216,805	2115	703.5	500
No. of counties with tweets		**Median**	**Maximum**	**75% Percentile**	**25% Percentile**	**Minimum**
	all, n=2,380 counties	82	340,717	530.8	22	1
	≥100 tweets, n=1,115 counties	629	340,717	2193	210	100
	≥500 tweets, n=605 counties	1892	340,717	5479	935	500

Total number of COVID-19-related tweets analyzed n=4,505,399

For aggregate analyses of Twitter communication (Figure 1), all tweets were analyzed. For analyses of Twitter communication in U.S. cities or counties, we only included communities for which at least 100 tweets, or at least 500 tweets, were recovered. Analyses using both minimum thresholds of tweets for each type of community were performed, and the results and conclusions were similar, indicating that the analysis of thousands of local communities is robust.

Automatic topic filters

To automatically detect and classify the major topics of COVID-19 communication on Twitter, we employed a closed-vocabulary approach to examine various topics within COVID-19 communication. The closed-vocabulary method of topic filtering on large text corpus has been long established and used by researchers who conducted content analysis research in communication (Schwartz & Ungar, 2015). The closed-vocabulary approach assumes that specific keywords as indicators can capture topics of the text. We began by carefully reading 2,000 randomly selected COVID-19-related tweets from a larger dataset. As a result, 13 distinct topics discussed in the COVID-19 context were identified. These topics were: masking, pro-masking (encouraging people to wear a mask), COVID-19 vaccination, healthcare and public health (not masking and vaccination-related), social aspects, economy, education, religion, race and ethnicity, politics, partisan or divisive language, conspiratorial language, and the use of foul words in COVID-19 communication. To develop the filters for pro-masking and conspiracies, we also included keywords that were previously identified and validated in the literature, specifically for COVID-19 communication (Lang et al., 2021; Motta et al., 2020). Then, all keywords for each of the 13 topic filters were applied to a randomly selected set of 1,000 tweets. The accuracy of each filter was manually assessed, and specific words were either added or removed to ensure that each filter was specific (it did not detect false positives or false negatives). Finally, the updated topic filters were applied to a new set of 2,000 randomly selected posts to examine the validity of each filter. This showed that the accuracy rate of all filters was between 93-98%, indicating that the automatic filter detection is robust and specific for all topics of COVID-19 communication.

Tweet sentiment analysis

Hyperlinks and mentions were removed before the sentiment analysis. The nltk sentiment Python package was used to obtain the sentiment score for each tweet. The sentiment scores span from -1 (negative), 0 (neutral), to +1 (positive).

Retrieval of tweets posted by the media

The Academic Twitter Application Programming Interface and Python's request package were used to retrieve tweets. We collected all tweets posted on the Twitter accounts of CNN, Fox News, MSNBC, ABC News and NBC News between January 1, 2020, and December 31, 2022.

Retrieval of tweets posted by the media and political candidates

The Academic Twitter Application Programming Interface and Python's request package were used to retrieve tweets. Audience metrics (the number of likes/favorites, retweets, and comments) were extracted seven days after a tweet was posed to ensure equal audience exposure time for further engagement analysis. News media entities analyzed were the Twitter accounts of CNN, Fox News, MSNBC, ABC News, NBC News, and CBS News.

To retrieve tweets for the candidates that competed for the 435 seats in the U.S. House of Representatives in the 2022 midterm elections, the candidate’s name, political party affiliation, seat district, and Twitter handles were first collected (*Members’ Official Twitter Handles*, 2022). In total, we identified 965 candidates that competed for the 435 seats in the U.S. House of Representatives. Of these, n=854 (88%) had Twitter accounts and were included in the analysis. FiveThirtyEight, a website for opinion polling operated by ABC News, was consulted to access information about races in each district, including information on the candidates for each House seat, as well as the incumbents. House incumbents who were not seeking reelections (*n*=56) were excluded from the analysis. The Academic Twitter Application Programming Interface and Python's request package were used to retrieve tweets from the 854 Twitter handles. The tweets were scraped every night around 11 p.m. and seven days after they were posted. All tweets were posted from September 1, 2022, to November 15, 2022, two weeks after the midterm elections. Audience metrics (the number of likes, retweets, and comments), user profile information (id, follower number at the moment of scraping), and tweet features (containing multimedia) were recorded for each tweet.

Analysis of audience engagement with politicians' tweets

For each candidate, we computed an average engagement score for topic COVID-19 by dividing the mean engagement of COVID-19-related tweets by the mean engagement of all tweets posted by the candidate. A Wilcoxon test was used to assess whether the engagement by a group of candidates (winners, losers) was statistically different (either higher or lower) than a value of 1, representing the average engagement of all topics taken in aggregate.

Statistics

For comparing the means of two groups, two-tailed, unpaired t-tests were conducted. For comparing the means of 3 or more groups, one-way ANOVA with Tukey's post-hoc test (for Gaussian distributions) or Kruskall-Wallis one-way ANOVA for non-Gaussian distributions were employed. Spearman (for non-Gaussian distributions) regression analyses were used to examine the relationship between individual variables. Multivariate regression analyses were conducted to model the contribution of several independent variables to selected dependent variables. Negative Binomial regression analyses were employed for count data. Before building regression models, the multicollinearity among the independent variables, using the variance inflation factor (VIF), was assessed. Variables with a high degree of multicollinearity were excluded from the models. Regression analyses were performed using the IBM SPSS Statistics 28.0 software.

RESULTS

Local political ideology and COVID-19 Twitter Communication

To answer our first RQ, we began by filtering all COVID-19-related tweets collected over the first three years of the COVID-19 pandemic. When analyzing the prevalence of COVID-19-related topics, we found that, taken in aggregate over three years, the most common topics employed in COVID-19 communication by the sampled Twitter users were social aspects (30.3%), such as social gatherings, family reunions, birthday celebrations. Topics related to healthcare and public health (28%), as well as topics related to wearing a mask to prevent COVID-19 transmission (20.3%) and vaccination against the coronavirus (16.4%) were the most prominent aspects of COVID-19 communication on Twitter. Political issues were communicated in 13.7% of all tweets, while very few tweets featured partisan or divisive language (1.1%) or conspiratorial language (0.6%). The economy was mentioned in 5.7% of the tweets, education in 3.2% and religion in 1.1% of the tweets. Finally, 5.7% of all tweets included foul words (Figure 1).

Figure 1. Topic usage in COVID-19 Twitter communication of Americans

Topic	Prevalence
Masking (all)	20.3%
Pro-masking	1.3%
Vaccination	16.4%
Healthcare, public health	28.0%
Social aspects	30.3%
Economy	5.7%
Religion	1.1%
Race, ethnicity	1.1%
Education	3.2%
Politics	13.7%
Partisan, divisive language	1.1%
Conspiracies	0.6%
Foul words	5.7%

	20-2	20-3	20-4	20-5	20-6	20-7	20-8	20-9	20-10	20-11	20-12
Masking (all)	21.6	3.4	9.6	19.0	30.8	33.8	26.6	27.4	24.4	22.5	17.3
Pro-masking	0.0	0.1	0.2	0.8	2.8	4.2	2.9	2.9	2.9	3.5	2.5
Vaccination	6.5	1.1	1.5	2.2	1.8	2.4	3.0	4.5	2.6	7.1	20.0
Healthcare, public health	24.1	54.5	55.2	44.1	32.2	29.7	26.8	25.4	26.5	28.4	25.5
Social aspects	24.5	32.8	33.1	32.9	33.8	31.6	33.6	31.4	25.1	31.5	31.6
Economy	5.1	5.2	5.6	6.0	5.4	5.6	6.2	6.7	5.4	5.5	7.3
Religion	1.0	1.0	1.1	1.1	1.0	1.0	1.0	0.9	1.2	1.3	1.3
Race, ethnicity	1.1	0.8	0.8	1.4	3.6	1.7	1.8	1.4	1.0	1.0	0.9
Education	1.9	2.6	2.2	2.5	2.2	3.3	5.3	4.4	2.6	2.8	2.8
Politics	13.1	9.6	9.9	12.3	15.5	16.9	16.4	19.8	30.4	21.6	16.6
Partisan, divisive language	1.5	0.7	0.6	0.8	1.3	1.5	1.3	1.6	2.0	1.4	1.2
Conspiracies	1.3	1.7	0.7	0.6	0.7	0.8	0.9	0.7	0.8	0.5	0.6
Foul words	5.6	6.7	6.0	5.9	7.4	7.2	6.4	6.4	6.6	6.8	6.7
Mean sentiment of tweets	0.00	0.07	0.09	0.08	0.04	0.04	0.06	0.03	0.03	0.04	0.05

	21-1	21-2	21-3	21-4	21-5	21-6	21-7	21-8	21-9	21-10	21-11	21-12
Masking (all)	18.3	17.7	19.8	17.9	26.6	19.3	20.3	22.7	18.5	16.5	15.2	13.6
Pro-masking	1.8	1.5	1.6	1.2	1.0	0.6	1.3	1.8	1.2	0.8	0.9	0.8
Vaccination	19.5	21.0	30.7	37.4	30.5	23.9	35.0	34.2	34.3	33.8	32.0	22.5
Healthcare, public health	23.3	22.1	22.6	23.7	24.7	24.2	28.5	29.0	26.9	26.9	24.6	26.2
Social aspects	29.8	31.6	28.7	27.5	29.0	29.8	27.7	29.7	30.1	29.3	28.8	28.5
Economy	5.6	6.5	6.2	4.4	5.1	5.4	4.7	4.0	4.9	5.4	5.6	4.5
Religion	1.1	1.0	0.9	1.1	1.0	0.9	1.1	1.4	1.5	1.4	1.3	1.0
Race, ethnicity	1.1	1.2	1.4	1.1	1.2	1.0	0.8	0.7	0.9	0.9	0.8	0.5
Education	3.5	4.6	3.3	3.0	3.3	2.9	2.7	5.2	4.6	3.6	2.8	2.2
Politics	15.3	13.3	13.9	9.6	11.1	10.7	14.7	15.2	14.8	13.4	12.6	10.7
Partisan, divisive language	1.1	0.7	0.7	0.7	0.9	0.9	1.3	1.1	1.2	1.1	1.2	0.9
Conspiracies	0.6	0.4	0.7	0.4	0.6	0.5	0.4	0.4	0.4	0.4	0.4	0.3
Foul words	6.1	5.3	5.3	5.2	5.3	5.1	6.2	6.3	6.2	5.4	5.0	6.2
Mean sentiment of tweets	0.05	0.07	0.08	0.07	0.07	0.05	0.00	0.00	0.00	0.00	0.02	0.02

	22-1	22-2	22-3	22-4	22-5	22-6	22-7	22-8	22-9	22-10	22-11	22-12
Masking (all)	14.9	26.7	24.5	28.8	18.3	17.0	17.9	15.3	16.9	19.0	18.1	16.7
Pro-masking	0.7	0.8	0.8	1.0	0.7	0.6	0.7	0.4	0.7	0.6	0.6	0.9
Vaccination	18.6	16.7	13.2	11.6	13.3	14.0	14.4	14.3	16.4	17.2	11.9	13.3
Healthcare, public health	26.7	26.2	24.6	27.0	25.4	25.1	25.7	28.0	25.3	24.6	25.6	29.1
Social aspects	30.1	31.4	32.1	33.1	32.3	31.9	28.9	31.7	30.2	29.6	31.1	30.4
Economy	4.8	5.9	7.3	6.2	7.2	7.7	6.5	7.9	7.2	6.3	5.7	4.8
Religion	1.2	1.1	1.0	0.9	1.0	1.1	1.1	1.1	0.9	0.9	1.0	1.1
Race, ethnicity	0.7	1.1	0.9	0.7	0.9	0.9	0.8	0.8	0.8	0.9	0.9	0.7
Education	3.9	3.9	3.5	2.9	3.6	2.6	2.2	3.9	3.8	3.7	3.1	2.3
Politics	12.3	13.2	13.0	12.3	12.2	12.3	14.1	14.8	14.1	11.2	11.9	11.1
Partisan, divisive language	1.0	1.2	1.0	0.8	0.8	1.0	1.3	1.3	1.3	1.0	1.1	1.4
Conspiracies	0.3	0.4	0.4	0.3	0.5	0.3	0.4	0.4	0.3	0.4	0.5	0.8
Foul words	5.6	4.6	4.5	4.7	5.2	5.2	5.3	5.3	5.0	4.7	5.6	5.7
Mean sentiment of tweets	0.02	0.02	0.03	0.04	0.03	0.03	0.02	0.02	0.01	0.02	0.01	0.02

Note. The top panel represents the average topic prevalence from late January 2020 until December 31, 2022. Note that some tweets featured more than one topic. The bottom panel shows the evolution of monthly topic usage (in %) from February 1, 2020 (20-2) until December 31, 2022 (22-12). The darker the color indicates a higher percentage of a topic weight in the COVID-19 Twitter communication in the dataset. For mean tweet sentiment, a positive sentiment (score >0) is shaded in pink, and a negative sentiment (score <0) is shaded in blue.

https://doi.org/10.33774/apsa-2024-hf7gf **ORCID:** https://orcid.org/0000-0002-7221-5495

We then examined the temporal evolution of topic usage during the first three years of the pandemic. Mentions of healthcare and public health issues peaked at 54-55% of all tweets in March and April 2020, after which they were steadily present in about 25-30% of all tweets. Social aspects were discussed in about 30% of all tweets throughout the pandemic. Tweets about mask wearing represented about 30% of all tweets in summer 2020 and then slightly declined to about 15-20% of all tweets, with the exception of February-April 2022 when they represented 26-28% of all tweets. Tweets about COVID-19 vaccination were most prevalent (up to 37%) in spring 2021, when the national COVID-19 vaccination campaign debuted in the U.S. Political aspects of the pandemic were most prevalent (30.4%) in October 2020, right before the presidential elections. Overall, the tone of all COVID-19-related tweets was mildly positive (mean tweet sentiment 0.03 to 0.09 between spring 2020 and spring 2021) and again in late 2021 and early-mid 2022. The overall tone became neutral (sentiment score close to zero) in summer 2021, when the delta variant emerged (Figure 1).

We then determined the average tone of each COVID-19 topic (Figure 2). We found that topics related to pro-masking, education and religion were communicated in a mostly positive tone, whereas tweets featuring race and ethnicity, conspiracies and politics were mostly negative. As expected, the presence of foul words denoted a negative tweet sentiment (Figure 2).

Figure 2. The emotional tone of COVID-19-related topics

	All cities
Pro-masking	0.14
Education	0.14
Religion	0.12
Social	0.08
Healthcare public health	0.07
Masking (all tweets)	0.05
Economy	0.05
Vaccination	0.03
Anti-masking	-0.02
Politics	-0.08
Law enforcement	-0.14
Extremism and conspiracy	-0.19
Race ethnicity	-0.19
Foul words	-0.37

Note. The shading represents the average degree of positivity (orange) or negativity (green) in communicating each topic.

To answer RQ1 and determine whether the political ideology of U.S. counties and cities predicts topic usage by members of communities, we assessed the correlation between the ideological score of communities and the prevalence of topic usage on Twitter by users residing in the communities (Figure 3 and Supplementary Figure 1).

We found that local political ideology was a significant predictor of topic usage on Twitter (Figure 3). Thus, Twitter users from liberal counties and cities tweeted more about race and ethnicity, and social aspects, less about masking, religion and conspiracies about COVID-19. A longitudinal analysis showed that citizens in the most liberal cities tweeted less about masking in the early phases of the pandemic (mid 2020 to early 2021; Supplementary Figure 2). Citizens from the most liberal cities also tweeted more about vaccination in April-June 2021, when widespread vaccination was introduced in the U.S.; Supplementary Figure 3).

By contrast, users from conservative counties and cities were more likely to tweet about religious issues and used significantly fewer foul words in their tweets.

Citizens in the most liberal cities also tweeted more positively about COVID-19 during several months of the pandemic (Supplementary Figure 4), suggesting that these communities maintained a more upbeat outlook during certain periods of the pandemic.

Overall, the correlation between local ideology and topic usage was more significant in counties compared to cities (Figure 3 and Supplementary Figure 1), reflecting the fact that more tweets were sampled in the larger counties. Some of the weaker correlations between local ideology and topic usage were only significant for county tweet data and only when all counties (conservative and liberal) were taken in aggregate – for example a higher mrp score, denoting a more conservative ideology, predicted less mentions of pro-masking, vaccination and the economy, and a more negative tweet sentiment (Figure 3). Taken together, these findings identify a close correlation between local political ideology and COVID-19 communication on Twitter.

Figure 3. The political ideology of U.S. communities predicted their COVID-19 topic usage and sentiment on Twitter.

Correlation between county ideology and COVID-19 communication topic usage									
	All counties			Liberal* (-mrp>0)			Conservative (mrp>0)		
COVID-19 communication	r	P value	Sig	r	P value	Sig	r	P value	Sig
Masking (all)	**0.343**	**P<10-15**	****	**-0.359**	**7E-10**	****	**0.112**	**0.044**	*
Pro-masking	**-0.129**	**0.0015**	**	0.061	0.31	ns	0.009	0.87	ns
Vaccination	**-0.114**	**0.005**	**	0.077	0.20	ns	-0.088	0.11	ns
Healthcare, public health	-0.006	0.88	ns	-0.007	0.91	ns	0.012	0.83	ns
Social aspects	**-0.216**	**8E-08**	****	**0.142**	**0.018**	*	-0.108	0.0519	ns
Economy	**-0.114**	**0.0049**	**	0.112	0.063	ns	-0.032	0.57	ns
Religion	**0.299**	**6E-14**	****	**-0.170**	**0.004**	**	**0.125**	**0.024**	*
Race, ethnicity	**-0.284**	**1E-12**	****	**0.387**	**2E-11**	****	-0.061	0.27	ns
Education	**0.103**	**0.011**	*	**-0.149**	**0.0125**	*	0.029	0.61	ns
Politics	0.021	0.60	ns	-0.111	0.063	ns	-0.041	0.46	ns
Partisan, divisive language	0.006	0.88	ns	-0.017	0.77	ns	-0.026	0.64	ns
Conspiracies	**0.129**	**0.0015**	**	**-0.123**	**0.0398**	*	0.090	0.106	ns
Foul words	-0.050	0.22	ns	**-0.178**	**0.0029**	**	-0.068	0.22	ns
Mean sentiment of tweets	**-0.139**	**0.0006**	***	0.109	0.068	ns	-0.024	0.66	ns

Correlation between city ideology and COVID-19 communication topic usage									
	All cities			Liberal* (-mrp>0)			Conservative (mrp>0)		
COVID-19 communication	r	P value	Sig	r	P value	Sig	r	P value	Sig
Masking (all)	**0.293**	**P<10-15**	****	**-0.246**	**9E-14**	****	0.011	0.85	ns
Pro-masking	-0.043	0.14	ns	0.019	0.56	ns	-0.006	0.91	ns
Vaccination	0.014	0.62	ns	-0.031	0.35	ns	0.024	0.68	ns
Healthcare, public health	-0.011	0.70	ns	0.011	0.75	ns	-0.012	0.83	ns
Social aspects	**-0.116**	**6E-05**	****	**0.129**	**0.0001**	***	-0.087	0.13	ns
Economy	-0.025	0.39	ns	0.034	0.32	ns	0.022	0.71	ns
Religion	**0.259**	**P<10-15**	****	**-0.170**	**3E-07**	****	**0.166**	**0.004**	**
Race, ethnicity	**-0.230**	**1E-15**	****	**0.263**	**2E-15**	****	0.013	0.82	ns
Education	**0.129**	**7E-06**	****	-0.014	0.68	ns	0.087	0.13	ns
Politics	**0.106**	**0.0003**	***	**-0.097**	**0.004**	**	0.020	0.72	ns
Partisan, divisive language	0.039	0.18	ns	-0.010	0.76	ns	0.024	0.68	ns
Conspiracies	**0.141**	**1E-06**	****	**-0.132**	**8E-05**	****	**0.114**	**0.0492**	*
Foul words	-0.045	0.12	ns	**-0.087**	**0.009**	**	**-0.162**	**0.0050**	**
Mean sentiment of tweets	**-0.113**	**1E-04**	****	**0.098**	**0.003**	**	-0.035	0.55	ns

Note. Shown are the Spearman correlation coefficients (r) between the mrp scores of U.S. counties (top) or cities (bottom) and the COVID-19 topic usage on Twitter by users located in each county or city, between late January 2020 and December 31, 2022. Counties and cities for which at least 500 tweets were collected were included in the analysis. An analysis of counties with at least 100 tweets yielded similar conclusions (see Supplementary Figure 1). * a negative mrp score (-mrp) was used in correlations for liberal counties or cities only, to assess correlations between increasing liberal ideology and COVID-19 topic usage.

Socio-economic determinants of COVID-19 communication on Twitter

To answer RQ2, we then assessed whether people residing in different communities talked differently about COVID-19 on Twitter. Figure 4 shows that, compared to the national average (all counties), users residing in graying America tweeted more about politics, used more partisan and divisive language and were twice as likely to mention COVID-19-related conspiracy theories. Residents of rural middle America, working class country and Evangelical hubs also tweeted more conspiracies, while tweeting less about race and ethnicity. Users from Evangelical hubs and college towns tweeted more about education, while residents of Evangelical hubs, working class counties and the African American south tweeted more about religion.

Figure 4. Topic usage in COVID-19 Twitter communication in American communities

	Masking (all)	Pro-masking	Vaccination	Healthcare, public health	Social aspects	Economy	Religion	Race, ethnicity	Education	Politics	Partisan, divisive language	Conspiracies	Foul words
All counties	**20.26**	**1.28**	**16.4**	**28.0**	**30.3**	**5.75**	**1.08**	**1.06**	**3.22**	**13.7**	**1.10**	**0.63**	**5.74**
Big cities	20.45	1.34	16.2	27.7	31.0	5.81	0.99	1.18	2.87	12.8	1.03	0.54	5.89
Urban burbs	19.52	1.25	16.5	28.5	29.7	5.83	1.10	0.99	3.33	14.9	1.17	0.71	5.52
College towns	20.12	1.13	16.7	28.5	30.5	5.78	1.10	0.91	4.96	14.5	1.09	0.65	5.05
Hispanic centers	18.38	1.12	14.9	25.7	28.7	5.03	1.14	0.98	3.18	12.9	1.18	0.61	6.79
African American South	21.92	1.05	16.0	27.7	29.9	5.12	1.57	0.97	4.00	12.4	0.90	0.65	6.03
Exurbs	20.81	1.41	17.4	29.4	30.0	5.91	1.15	0.85	3.37	16.2	1.23	0.72	5.28
LDS enclaves	24.28	1.06	15.8	26.2	29.0	5.15	1.10	0.91	2.82	12.8	1.18	0.52	4.69
Middle suburbs	21.40	1.01	17.0	27.9	29.3	5.42	1.21	0.90	3.11	15.2	1.27	0.76	6.08
Graying America	20.19	1.52	17.8	30.5	28.6	5.98	1.25	0.85	2.80	19.1	1.72	1.21	5.90
Military posts	21.34	1.18	16.3	27.5	28.7	5.83	1.32	0.98	3.37	14.4	1.23	0.64	6.01
Rural middle America	19.34	1.12	16.5	28.6	29.8	5.68	1.14	0.70	3.96	15.6	1.38	0.98	5.47
Working class country	20.86	0.94	17.3	30.1	27.1	5.28	1.77	0.70	3.63	13.7	0.97	1.17	5.38
Evangelical hubs	19.87	1.05	16.9	28.5	29.9	5.30	2.04	0.65	5.61	14.1	1.16	0.88	4.49

Note. The topic usage averages for each type of community are shown as percentages.

The visualization of the monthly evolution of topic usage further showed that COVID-19 communication in some communities – in particular graying America, rural middle America and working class country – was more politicized, more partisan and divisive and employed more conspiratorial language, especially between summer 2021 and spring-summer 2022. Working class counties also communicated more conspiracy theories during most months (Figure 5).

Figure 5. Evolution of the use of COVID-19-related politicized, partisan and conspiratorial language in American communities

Politicized COVID-19-related tweets (%)

	20-2	20-3	20-4	20-5	20-6	20-7	20-8	20-9	20-10	20-11	20-12	21-1	21-2	21-3	21-4	21-5	21-6	21-7	21-8	21-9	21-10	21-11	21-12	22-1	22-2	22-3	22-4	22-5	22-6	22-7	22-8	22-9	22-10	22-11	22-12
All counties	**13.1**	**9.6**	**9.9**	**12.3**	**15.5**	**16.9**	**16.4**	**19.8**	**30.4**	**21.6**	**16.6**	**15.3**	**13.3**	**13.9**	**9.6**	**11.1**	**10.7**	**14.7**	**15.2**	**14.8**	**13.4**	**12.6**	**10.7**	**12.3**	**13.2**	**13.0**	**12.3**	**12.2**	**12.3**	**14.1**	**14.8**	**14.1**	**11.2**	**11.9**	**11.1**
Big cities	12.0	9.1	9.1	11.3	15.1	16.0	16.1	19.0	29.8	21.0	15.6	14.6	12.3	13.1	8.7	10.3	9.8	12.8	14.1	13.2	12.2	11.7	9.8	11.3	12.3	11.9	11.1	11.1	11.2	12.4	13.5	13.0	9.4	11.4	10.4
Urban burbs	14.0	10.4	10.9	13.5	16.0	17.8	16.5	22.0	31.5	23.3	18.2	16.3	15.1	14.7	10.5	11.6	11.9	17.0	17.0	16.4	14.6	12.6	11.0	13.6	14.9	14.4	12.8	12.3	13.0	17.3	16.2	16.2	13.9	12.7	10.7
College towns	13.8	9.6	10.9	13.6	16.6	17.7	14.6	17.4	28.7	20.9	17.2	15.7	14.8	14.4	10.1	11.9	13.6	18.7	15.6	14.9	15.4	15.1	13.3	13.4	14.9	14.3	13.9	14.2	13.5	14.5	15.3	12.1	11.5	12.2	12.8
Hispanic centers	8.7	7.8	8.5	12.7	13.7	15.6	16.8	18.7	28.5	20.2	15.1	13.4	13.6	14.7	8.4	10.8	8.4	12.9	14.2	14.8	13.7	10.7	10.3	9.5	9.7	10.3	14.4	15.8	11.3	11.4	17.5	14.0	11.5	10.6	12.9
African American South	12.0	9.5	8.8	10.3	13.4	15.2	13.5	14.9	28.4	19.0	14.7	12.8	11.1	15.4	11.9	12.2	8.3	13.3	12.8	14.0	11.8	13.3	10.9	13.1	11.4	12.1	11.9	10.7	9.3	14.6	13.2	9.9	6.4	11.6	9.2
Exurbs	17.2	11.1	11.0	13.9	16.7	19.3	19.8	22.9	33.6	23.6	18.7	18.2	14.4	16.1	11.0	12.7	12.9	16.8	17.8	17.5	15.9	15.0	13.3	13.1	14.0	16.8	15.4	18.5	14.7	18.2	18.2	15.2	15.6	14.8	12.3
LDS enclaves	15.9	9.0	10.1	13.8	19.7	19.8	17.8	16.8	21.6	13.1	14.8	12.3	10.7	8.8	10.5	12.2	9.0	20.3	18.3	19.0	11.4	10.1	9.6	13.7	11.5	15.5	10.7	9.1	9.7	13.5	7.8	12.3	12.2	12.4	5.1
Middle suburbs	15.2	10.7	11.2	14.0	17.2	18.7	17.5	22.5	32.8	23.6	17.2	16.3	15.4	15.6	10.6	11.3	13.0	17.5	16.4	18.1	13.2	14.7	10.9	14.0	14.4	15.1	13.9	15.0	16.1	15.2	16.5	14.4	9.7	10.8	11.0
Graying America	21.0	14.3	13.4	16.0	17.4	23.0	21.5	25.9	37.0	29.2	24.0	19.8	17.4	19.1	11.9	16.3	16.3	23.2	21.1	21.3	18.7	18.8	19.2	16.0	18.8	15.5	19.9	15.0	19.1	18.0	24.0	24.7	16.0	16.0	17.3
Military posts	14.8	8.3	9.2	11.7	16.0	15.5	16.3	21.0	30.8	21.2	16.8	16.2	11.6	14.8	10.5	10.3	9.5	15.2	15.0	15.6	13.3	16.3	11.4	12.2	11.4	14.4	14.8	10.6	15.4	17.4	16.9	24.0	14.5	6.7	13.3
Rural middle America	21.3	9.3	11.1	16.3	17.0	17.2	17.9	21.4	31.5	20.1	18.3	18.2	13.6	15.0	10.6	12.9	11.8	15.9	13.8	15.6	11.1	11.3	11.6	14.3	17.3	16.1	15.9	16.6	18.7	16.8	16.3	14.1	17.2	15.2	13.1
Working class country	13.5	7.3	9.7	11.2	11.4	14.6	14.2	17.1	30.9	19.0	14.3	14.9	12.8	12.8	8.7	10.4	8.5	14.0	13.0	13.3	16.8	14.8	15.0	12.8	15.2	18.9	20.2	18.0	22.2	16.7	12.6	10.9	6.6	7.6	9.9
Evangelical hubs	11.5	11.1	14.5	19.1	16.0	17.6	15.4	21.7	27.9	20.6	16.8	12.0	7.6	11.2	11.2	11.4	9.0	13.7	16.9	19.6	16.5	12.4	10.9	13.0	16.7	19.1	23.4	18.3	12.7	10.9	7.2	11.5	9.5	5.7	16.4

COVID-19-related tweets containing partisan and divisive language (%)

	20-2	20-3	20-4	20-5	20-6	20-7	20-8	20-9	20-10	20-11	20-12	21-1	21-2	21-3	21-4	21-5	21-6	21-7	21-8	21-9	21-10	21-11	21-12	22-1	22-2	22-3	22-4	22-5	22-6	22-7	22-8	22-9	22-10	22-11	22-12
All counties	**1.46**	**0.66**	**0.62**	**0.81**	**1.26**	**1.51**	**1.28**	**1.63**	**2.02**	**1.35**	**1.24**	**1.13**	**0.71**	**0.69**	**0.70**	**0.85**	**0.87**	**1.30**	**1.12**	**1.21**	**1.10**	**1.21**	**0.88**	**1.03**	**1.21**	**1.04**	**0.83**	**0.83**	**1.00**	**1.26**	**1.31**	**1.27**	**1.03**	**1.08**	**1.41**
Big cities	1.43	0.62	0.59	0.78	1.20	1.50	1.31	1.56	2.02	1.34	1.21	1.13	0.68	0.62	0.59	0.76	0.76	1.27	1.04	1.10	0.98	1.18	0.84	1.00	1.10	1.08	0.76	0.74	0.95	1.02	1.15	1.23	0.72	0.99	1.11
Urban burbs	1.65	0.71	0.62	0.81	1.32	1.44	1.20	1.58	1.90	1.45	1.20	1.18	0.73	0.74	0.78	0.81	1.01	1.20	1.24	1.37	1.20	1.26	0.85	1.09	1.59	1.07	0.78	0.88	0.94	1.81	1.69	1.29	1.16	1.19	1.53
College towns	1.25	0.66	0.89	1.03	1.28	1.52	1.28	1.82	1.91	1.09	1.22	0.92	0.68	0.71	0.66	1.10	1.12	0.98	1.05	1.06	1.18	1.33	0.69	0.70	1.36	0.66	0.94	0.82	0.89	1.36	1.05	0.90	1.28	0.64	2.52
Hispanic centers	0.67	0.71	0.70	0.83	1.20	1.57	1.45	2.14	2.34	1.46	1.47	0.92	0.59	0.96	0.61	1.06	0.64	1.18	1.01	2.02	0.91	1.09	0.78	1.14	1.13	1.16	1.15	2.13	0.55	1.87	1.52	1.34	1.00	1.02	1.97
African American South	1.47	0.63	0.50	0.82	1.08	1.30	0.92	1.20	1.99	1.18	1.37	0.84	0.74	0.55	0.78	0.92	0.42	1.84	0.82	0.82	0.99	0.79	0.91	0.91	0.33	0.52	0.28	0.55	0.90	0.63	0.64	1.32	0.49	0.81	1.03
Exurbs	1.25	0.74	0.53	0.74	1.27	1.72	1.28	1.74	2.16	1.21	1.45	1.16	0.62	1.01	0.98	1.07	0.83	1.41	1.21	1.19	1.37	1.14	1.01	1.07	1.44	0.87	0.89	0.65	1.52	1.59	1.66	1.29	1.47	1.23	2.20
LDS enclaves	1.22	0.54	0.34	0.59	1.83	1.28	1.93	1.88	1.42	1.16	1.09	1.06	0.73	0.85	1.20	0.88	0.71	1.60	1.49	1.39	0.21	1.09	1.55	1.63	0.96	0.52	0.93	0.57	0.54	0.77	3.11	0.51	3.06	1.90	2.04
Middle suburbs	1.57	0.62	0.62	0.72	1.62	1.57	1.06	1.19	1.97	1.79	1.38	0.99	1.19	0.79	0.88	0.97	2.26	2.38	2.13	1.83	1.57	0.85	1.14	1.24	0.64	0.68	1.70	0.66	1.65	1.15	1.66	1.32	1.61	1.01	1.38
Graying America	3.55	0.92	1.23	1.47	1.40	2.08	1.76	2.28	2.73	1.90	1.59	1.49	1.46	1.14	1.20	1.25	1.93	2.20	1.61	1.63	1.51	2.25	1.81	1.53	1.89	1.74	1.30	1.20	1.58	1.57	0.89	1.47	4.28	2.13	1.37
Military posts	1.96	0.60	0.55	0.99	1.68	1.33	1.12	1.47	2.54	1.27	1.05	1.69	0.56	0.55	0.53	0.99	0.69	1.30	0.99	1.24	1.19	1.78	0.53	1.17	0.42	1.70	1.61	0.80	0.97	1.08	1.93	3.43	1.64	1.26	1.58
Rural middle America	1.50	0.66	0.59	0.83	1.99	1.82	1.46	2.33	2.11	1.27	1.11	1.17	0.79	0.79	1.33	1.44	0.34	1.80	1.16	0.75	1.84	1.36	1.20	0.95	0.64	0.68	1.59	1.23	3.12	1.59	1.88	2.19	1.21	1.72	1.99
Working class country	0.00	0.51	0.81	0.76	1.15	1.21	1.31	1.39	1.19	1.36	1.12	0.75	0.83	0.21	1.00	1.40	1.46	1.08	1.11	1.49	1.68	1.46	1.39	0.32	0.38	0.86	1.04	1.46	0.89	0.64	0.76	0.44	0.66	1.53	1.42
Evangelical hubs	1.15	0.77	0.50	0.33	0.64	1.35	0.86	2.14	1.63	1.56	0.77	1.25	0.56	0.44	0.96	0.45	1.20	1.07	0.55	0.40	1.42	0.59	1.82	2.68	4.17	3.37	0.00	4.88	0.00	0.00	0.80	0.00	1.59	0.00	1.82

COVID-19 related tweets containing conspiratorial language (%)

	20-2	20-3	20-4	20-5	20-6	20-7	20-8	20-9	20-10	20-11	20-12	21-1	21-2	21-3	21-4	21-5	21-6	21-7	21-8	21-9	21-10	21-11	21-12	22-1	22-2	22-3	22-4	22-5	22-6	22-7	22-8	22-9	22-10	22-11	22-12
All counties	**1.28**	**1.71**	**0.66**	**0.63**	**0.73**	**0.79**	**0.86**	**0.70**	**0.78**	**0.50**	**0.55**	**0.64**	**0.44**	**0.66**	**0.43**	**0.58**	**0.52**	**0.42**	**0.38**	**0.41**	**0.40**	**0.41**	**0.33**	**0.32**	**0.41**	**0.36**	**0.32**	**0.48**	**0.35**	**0.36**	**0.41**	**0.32**	**0.39**	**0.51**	**0.85**
Big cities	1.09	1.46	0.55	0.52	0.58	0.65	0.75	0.54	0.67	0.42	0.46	0.52	0.39	0.59	0.40	0.52	0.49	0.38	0.34	0.32	0.37	0.36	0.31	0.29	0.32	0.32	0.24	0.34	0.23	0.28	0.29	0.34	0.24	0.42	0.79
Urban burbs	1.69	2.01	0.67	0.75	0.97	0.98	1.02	0.95	0.88	0.53	0.63	0.66	0.41	0.82	0.41	0.65	0.60	0.46	0.44	0.60	0.44	0.53	0.34	0.42	0.51	0.35	0.35	0.61	0.43	0.48	0.52	0.26	0.46	0.23	0.94
College towns	1.19	1.59	0.74	0.65	0.79	0.76	0.63	0.55	0.70	0.50	0.65	0.75	0.41	0.45	0.59	0.52	0.60	0.35	0.29	0.28	0.28	0.33	0.31	0.19	0.48	0.66	0.52	0.53	0.32	0.18	0.60	0.17	0.82	1.49	0.46
Hispanic centers	0.38	2.33	0.88	0.84	0.85	0.81	1.05	1.23	1.03	0.55	0.77	0.51	0.46	0.96	0.61	0.55	0.09	0.36	0.25	0.40	0.58	0.26	0.30	0.43	0.56	0.36	0.38	1.02	0.18	0.15	0.34	0.29	0.33	0.44	0.56
African American South	1.68	1.48	0.48	0.52	0.80	0.65	0.59	0.90	0.82	0.39	0.52	0.88	0.35	0.65	0.51	0.75	0.54	0.36	0.15	0.24	0.45	0.54	0.41	0.19	0.22	0.26	0.00	0.82	0.30	0.21	1.40	0.40	0.24	1.08	1.03
Exurbs	1.73	2.00	0.74	0.75	0.70	0.93	1.23	0.81	0.85	0.48	0.65	0.77	0.47	0.57	0.38	0.44	0.32	0.40	0.32	0.36	0.32	0.40	0.45	0.27	0.34	0.37	0.57	0.77	1.01	0.51	0.37	0.26	0.34	1.36	1.10
LDS enclaves	1.22	1.86	1.13	1.08	0.73	0.55	0.91	0.75	0.26	0.17	0.42	0.71	0.27	0.51	0.53	0.59	0.48	0.49	0.75	0.63	0.21	0.22	0.42	0.41	0.00	0.00	0.93	0.57	0.00	0.77	0.00	0.00	0.00	0.00	0.00
Middle suburbs	1.31	1.78	0.54	0.57	0.80	1.09	1.28	0.54	0.58	0.62	0.49	0.85	0.33	0.66	0.34	1.10	1.04	0.71	0.58	0.50	0.43	0.43	0.29	0.37	0.26	1.03	0.31	0.50	0.82	0.43	1.36	0.95	1.07	0.68	0.83
Graying America	1.65	3.20	1.39	1.13	1.32	1.49	1.34	1.01	1.94	1.67	1.18	1.33	1.35	1.19	0.63	1.31	0.10	0.70	0.92	0.91	0.48	0.18	0.47	0.54	1.58	0.19	1.48	1.20	0.59	0.92	0.36	0.37	1.07	0.53	1.37
Military posts	1.40	1.85	0.69	0.83	0.91	0.60	0.79	0.60	0.79	0.63	0.43	0.84	0.34	0.65	0.13	0.30	0.69	0.27	0.33	0.41	0.43	0.21	0.42	0.16	0.42	0.34	0.18	0.00	0.32	0.92	0.00	0.76	0.66	0.84	1.90
Rural middle America	2.70	2.21	1.40	0.98	1.12	1.36	1.08	1.41	1.17	0.87	0.67	1.62	1.18	1.14	0.64	0.94	1.02	0.94	0.62	0.40	0.64	0.58	0.24	0.24	0.16	0.45	0.00	0.62	0.28	0.53	0.42	0.00	0.60	0.34	0.57
Working class country	0.00	1.51	0.99	1.37	1.85	1.87	1.11	0.70	1.72	0.68	0.75	0.84	1.30	0.83	0.72	1.00	1.17	1.20	0.71	0.81	1.12	1.94	0.50	0.48	0.76	0.86	0.52	2.91	3.11	1.61	0.38	0.00	0.66	0.00	1.42
Evangelical hubs	2.30	2.05	1.05	0.33	0.77	0.78	0.76	0.57	1.16	1.17	0.99	1.07	1.12	0.00	0.64	1.36	0.60	0.54	0.55	0.80	0.94	0.59	0.91	0.38	2.98	0.00	1.30	0.00	0.00	0.00	0.00	0.00	1.59	0.00	1.82

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We then examined the overall emotional tone of COVID-19 communication in different communities. In all communities, the tone of COVID-19 communication was mostly positive from spring 2020 to spring 2021. In summer 2021, when the delta variant began spreading, the tone was visibly less positive in all communities, with some communities (graying America, Evangelical hubs, middle suburbs) being mostly negative in their COVID-19 communication. The positive tone resumed in big cities, urban burbs and college towns by spring 2022, while it remained mixed in the other communities (Figure 6). Thus, the mood of COVID-19 communication was similarly positive in all U.S. communities in the early part of the pandemic, and diverged in the second part of the pandemic.

Figure 6. Evolution of COVID-19 tweet sentiment in American communities

	20-2	20-3	20-4	20-5	20-6	20-7	20-8	20-9	20-10	20-11	20-12	21-1	21-2	21-3	21-4	21-5	21-6	21-7	21-8	21-9	21-10	21-11	21-12	22-1	22-2	22-3	22-4	22-5	22-6	22-7	22-8	22-9	22-10	22-11	22-12
All counties	.00	.07	.09	.08	.04	.04	.06	.03	.03	.04	.05	.05	.07	.08	.07	.07	.05	.00	.00	-.01	.00	.02	.02	.02	.02	.03	.04	.03	.03	.02	.02	.01	.02	.01	.02
Big cities	.00	.07	.09	.09	.04	.05	.06	.03	.03	.05	.05	.05	.07	.08	.07	.07	.05	.01	.00	.00	.01	.03	.03	.03	.03	.04	.05	.03	.03	.03	.03	.02	.03	.02	.03
Urban burbs	.00	.07	.09	.08	.03	.04	.05	.03	.03	.04	.04	.04	.06	.07	.05	.06	.04	.00	-.01	-.02	-.01	.03	.02	.01	.02	.02	.03	.01	.03	.00	.01	-.01	.01	-.02	.01
College towns	.00	.07	.10	.08	.04	.05	.06	.05	.05	.06	.06	.07	.09	.08	.09	.08	.05	.01	.02	.01	.00	.05	.02	.02	.02	.03	.07	.03	.03	.04	.01	.00	.01	.01	.00
Hispanic centers	.02	.03	.07	.05	.02	.02	.04	.02	.02	.04	.02	.03	.05	.05	.04	.06	.03	-.02	-.01	-.05	-.02	-.04	-.02	.04	.00	.02	.01	.00	-.03	.03	-.01	.00	-.04	-.02	-.04
African American South	-.05	.05	.09	.07	.04	.03	.05	.03	.02	.04	.04	.05	.08	.06	.06	.02	.04	.02	-.01	-.01	.00	.01	.02	.02	-.01	.02	.03	.02	.08	.01	.00	.04	.04	.01	.01
Exurbs	.00	.08	.10	.08	.04	.04	.04	.02	.02	.04	.06	.05	.09	.07	.07	.06	.05	-.01	.00	-.02	.00	.01	.01	.03	.01	.03	.03	.02	-.02	.00	.02	.01	.00	.00	.01
LDS enclaves	.01	.08	.10	.09	.03	.06	.05	.01	.01	.02	.04	.04	.03	.07	.06	.04	.00	-.03	-.02	-.01	-.03	-.01	.01	.00	.02	.03	.01	.09	.00	.02	.03	.07	.14	.03	-.07
Middle suburbs	-.04	.06	.07	.06	.01	.02	.04	.04	.03	.04	.05	.06	.07	.08	.05	.06	.02	-.03	-.03	-.02	-.02	-.03	.00	-.01	.05	.01	.04	.04	.00	.01	-.02	.02	-.08	-.06	-.01
Graying America	-.07	.07	.08	.08	.03	.02	.05	.01	-.01	.01	.00	.02	.06	.06	.08	.05	.02	-.05	-.04	-.03	-.02	-.02	-.03	.02	.00	.04	-.01	-.03	.00	.03	-.03	.00	-.03	-.02	.01
Military posts	.00	.06	.08	.06	.02	.03	.03	.01	.03	.02	.02	.02	.06	.10	.10	.06	.04	.00	-.02	-.02	.00	.03	.02	.02	-.01	.02	.01	.01	.03	.02	.05	.00	-.01	.00	.01
Rural middle America	.02	.08	.10	.08	.04	.04	.04	.04	.02	.04	.05	.04	.08	.09	.06	.06	.03	-.01	.01	.02	-.01	.02	.01	.02	-.01	.00	.06	.00	-.02	.00	.00	-.04	-.08	.04	-.01
Working class country	.05	.06	.09	.07	.05	.02	.05	.07	.01	.05	.04	.06	.10	.12	.07	.07	.05	.00	.00	-.01	-.01	.01	-.03	-.01	-.03	.02	-.02	-.02	.01	-.01	.02	.05	.05	-.01	.00
Evangelical hubs	-.02	.08	.10	.05	.04	.04	.09	.06	.06	.08	.06	.07	.15	.09	.05	.07	.05	-.02	-.02	-.04	-.07	.06	.05	-.01	.05	.02	.05	-.01	.11	.07	.00	-.04	.02	.08	-.10

Note. The mean tweet sentiment, positive sentiment is shaded in red (score >0) and negative sentiment (score <0) is shaded in blue.

We next asked whether the socioeconomic situation of a city, such as education attainment, household median, employment situation, and public health insurance coverage, may predict the patterns of COVID-19 Twitter communication. Spearman correlations analyses uncovered significant relationships between a community's socioeconomic situation and its members' COVID-19 communication topical patterns. Figure 8 shows that cities with a higher percentage of the population holding a bachelor's degree or higher predict a higher usage of COVID-19 topics related to social aspects, pro-masking, education, vaccination, and less usage of religion and use of foul language.

Users from cities with higher median income tweeted more social aspects of the pandemic, pro-masking, and healthcare-related issues. They also tweeted less about education and religion-related issues and used less foul language in Twitter

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communication about COVID-19. The higher a city's employment rate, the more likely users from that city tweet about social aspects of the pandemic, pro-masking, and vaccination issues. Similarly, high employment rates also predict less use of foul language. Interestingly, higher public health coverage, such as Medicaid and Medicare, in a city predicts more foul language in COVID-19 tweets, and less focus on social aspects, education, and pro-masking messaging (Figure 7).

Figure 7. Socio-economic determinants of COVID-19 Twitter communication

	% with bachelor degree			household income			% employed			% with health coverage		
	r	P-value	Sig	r	P-value	Sig	r	P-value	Sig	r	P-value	Sig
Masking (all)	-0.05	0.064	ns	**-0.13**	**9E-06**	****	-0.02	0.57	ns	0.03	0.32	ns
Pro-masking	**0.25**	**<E-06**	****	**0.14**	**2E-06**	****	**0.16**	**<E-06**	****	**-0.16**	**<E-06**	****
Vaccination	**0.18**	**<E-06**	****	**0.06**	**0.027**	*	**0.06**	**0.04**	*	-0.05	0.1	ns
Healthcare, public health	0.03	0.36	ns	**0.14**	**<E-06**	****	0.01	0.72	ns	**-0.07**	**0.011**	*
Social aspects	**0.29**	**<E-06**	****	**0.15**	**<E-06**	****	**0.21**	**<E-06**	****	**-0.21**	**<E-06**	****
Economy	**0.11**	**0.0002**	***	0.04	0.14	ns	-0.02	0.49	ns	0.01	0.78	ns
Education	**0.23**	**<E-06**	****	**-0.1**	**0.0008**	***	0	0.98	ns	**-0.2**	**<E-06**	****
Race, ethnicity	**0.08**	**0.006**	**	**0.09**	**0.0027**	**	0.01	0.74	ns	0	0.98	ns
Religion	**-0.1**	**0.0004**	***	**-0.15**	**<E-06**	****	**-0.08**	**0.009**	**	0.05	0.077	ns
Politics	**0.13**	**5E-06**	****	**0.09**	**0.002**	**	-0.02	0.53	ns	0.03	0.39	ns
Conspiracies	0.01	0.68	ns	**0.06**	**0.037**	*	-0.02	0.53	ns	0.03	0.35	ns
Foul words	**-0.45**	**<E-06**	****	**-0.17**	**<E-06**	****	**-0.14**	**<E-06**	****	**0.31**	**<E-06**	****

Note. The orange shading indicates the strength of a positive correlation, whereas green shading indicates the strength of a negative correlation.

We next asked what COVID-19 topics were most engaging during the pandemic, and whether local political ideology predicted local audience engagement. Figure 8 shows that local audience reactions to COVID-19 communication by like-minded peers were strongly segregated along ideological lines. Followers of users in liberal and centric cities were very engaged by tweets about masking. Race and ethnicity were highly engaging for audiences in politically centrist and liberal, but not conservative, cities. Political aspects of COVID-19 were very engaging for users in liberal cities but were de-engaging in politically centrist and conservative cities. Tweets about education were engaging only for users in centric and conservative, but not liberal, cities. Finally, audiences across all cities, irrespective of political ideology, were de-engaged by conspiratorial language (Figure 8).

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Figure 8. The most engaging topics of COVID-19 communication

	All cities		Top liberal		Top centric		Top conservative	
	B	P-value	B	P-value	B	P-value	B	P-value
(Intercept)	2.708	0	2.532	0	1.562	0	1.601	0
Masking (all)	-0.187	0	0.488	0	0.638	0	-0.191	0
Pro-masking	-0.265	0	-1.077	0	-1.165	0	-0.028	0.66
Vaccination	0.101	0	0.178	0	-0.246	0	-0.094	<.001
Healthcare, public health	0.006	<.001	0.235	0	0.221	0	0.015	0.23
Social aspects	-0.06	0	0.207	0	0.066	<.001	0.085	<.001
Education	0.284	0	-0.29	0	0.403	0	0.677	0
Economy	0.05	0	-0.082	0	-0.028	0.11	-0.074	0.004
Religion	0.311	0	-0.021	0.32	0.184	<.001	0.89	0
Race, ethnicity	-0.138	0	0.002	0.91	1.895	0	-0.307	<.001
Politics	0.112	0	0.381	0	-0.581	0	-0.143	<.001
Conspiracies	-0.343	0	-0.983	0	-0.86	0	-0.332	<.001
Foul words	0.199	0	-0.579	0	0.178	0	-0.121	<.001

COVID-19 communication as predictor of pandemic outcomes

To answer RQ3, we built regression models of COVID-19 mortality in U.S. counties (dependent variable), which incorporated the topical usage of COVID-19 communication and socio-economic metrics that are known to be associated with COVID-19 mortality.

Figure 9 shows that several aspects of COVID-19 communication on Twitter were significant predictors of aggregated COVID-19 mortality in U.S. counties during the first three years of the pandemic. As expected, a county’s political ideology, the rate of infection, chronic diseases (diabetes and smoking), lower education, and higher local unemployment, as well as a higher segregation index, predicted a higher COVID-19 mortality.

Remarkably, after accounting for these local socioeconomic metrics, we found that discrete topics of COVID-19 communication were significant predictors of COVID-19 mortality. Thus, more frequent mentions of religious issues and conspiracy theories, as well as COVID-19 politicization, predicted higher COVID-19 mortality. By contrast, communication about a preventative measure – mask-wearing – as well as a more positive emotional tone of tweets predicted lower mortality rates (Figure 9).

Figure 9. COVID-19 Twitter communication predicts COVID-19 mortality in U.S. counties

Variable	Estimate	SE	P value	Sig
Intercept	0.145	0.090	0.107	ns
Masking (all)	**-0.154**	**0.071**	**0.030**	*
Pro-masking	0.180	0.271	0.508	ns
Vaccination	-0.034	0.122	0.781	ns
Healthcare, public health	-0.096	0.070	0.169	ns
Social issues	0.079	0.109	0.467	ns
Economy	-0.464	0.241	0.054	ns
Religion	**1.765**	**0.582**	**0.0025**	**
Race, ethnicity	-0.855	0.602	0.156	ns
Education	-0.087	0.227	0.701	ns
Politics	**0.182**	**0.087**	**0.036**	*
Partisan, divisive language	-0.661	0.516	0.200	ns
Conspiracies	**1.040**	**0.450**	**0.021**	*
Foul words	-0.327	0.199	0.101	ns
Mean tweet sentiment	**-0.308**	**0.109**	**0.0048**	**
COVID-19 cases (%)	0.002	0.001	0.021	*
COVID-19 vaccination (%)	7E-05	4E-04	0.855	ns
% Adults with Obesity	-0.005	0.001	5E-06	****
% Adults with Diabetes	0.011	0.004	0.0028	**
HIV Prevalence Rate	-8E-07	2E-05	0.958	ns
% Smokers	0.013	0.002	1E-15	****
Segregation index	0.168	0.048	0.0005	***
% Rural	-4E-04	3E-04	0.175	ns
Median Household Income	5E-08	3E-07	0.852	ns
Education_age25	-0.002	0.001	0.0006	***
% Unemployed	0.009	0.002	5E-05	****
% Uninsured	0.001	0.001	0.659	ns
County_mrp_ideology	0.157	0.032	9E-07	****

Degrees of freedom: 565. R^2=0.664

Note. A weighted multivariate regression model is shown. Sig – statistical significance * p<0.05, ** p<0.01, *** p<0.001, **** p<0.0001. SE- standard error.

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We next asked whether these effects are mediated by COVID-19 communication in liberal-leaning or conservative-leaning counties, or both. We thus built separate regression models for liberal leaning (mrp<0) and conservative leaning (mrp>0) counties (Figure 10).

Figure 10. COVID-19 Twitter communication predicts COVID-19 mortality in both liberal-leaning and conservative-leaning U.S. counties.

	All counties				Counties with mrp<0				Counties with mrp>0			
Variable	**Estimate**	**SE**	**P value**	**Sig**	**Estimate**	**SE**	**P value**	**Sig**	**Estimate**	**SE**	**P value**	**Sig**
Intercept	0.145	0.090	0.107	ns	0.043	0.134	0.749	ns	0.329	0.129	0.011208	*
Masking (all)	**-0.154**	**0.071**	**0.030**	*	**-0.435**	**0.178**	**0.0154**	*	-0.046	0.090	0.611	ns
Pro-masking	0.180	0.271	0.508	ns	0.072	0.464	0.877	ns	0.360	0.337	0.286	ns
Vaccination	-0.034	0.122	0.781	ns	**-0.491**	**0.172**	**0.0048**	**	**0.359**	**0.169**	**0.0341**	*
Healthcare, public health	-0.096	0.070	0.169	ns	-0.122	0.092	0.187	ns	-0.092	0.126	0.467	ns
Social issues	0.079	0.109	0.467	ns	0.171	0.175	0.331	ns	0.195	0.148	0.188	ns
Economy	-0.464	0.241	0.054	ns	**-0.972**	**0.339**	**0.0045**	**	-0.321	0.329	0.331	ns
Religion	**1.765**	**0.582**	**0.0025**	**	0.599	1.060	0.572	ns	**1.684**	**0.728**	**0.021**	*
Race, ethnicity	-0.855	0.602	0.156	ns	-0.653	0.788	0.408	ns	-1.499	0.930	0.108	ns
Education	-0.087	0.227	0.701	ns	-0.207	0.284	0.466	ns	0.203	0.392	0.605	ns
Politics	**0.182**	**0.087**	**0.036**	*	**0.438**	**0.140**	**0.0019**	**	0.181	0.113	0.111	ns
Partisan, divisive language	-0.661	0.516	0.200	ns	-1.345	0.809	0.098	ns	-0.433	0.649	0.505	ns
Conspiracies	**1.040**	**0.450**	**0.021**	*	0.703	0.737	0.341	ns	0.715	0.560	0.203	ns
Foul words	-0.327	0.199	0.101	ns	0.129	0.363	0.722	ns	-0.221	0.247	0.372	ns
Mean tweet sentiment	**-0.308**	**0.109**	**0.0048**	**	-0.243	0.163	0.136	ns	-0.262	0.157	0.095	ns
COVID-19 cases (%)	0.002	0.001	0.021	*	0.003	0.001	0.002	**	-0.001	0.001	0.526	ns
COVID-19 vaccination (%)	7E-05	4E-04	0.855	ns	0.001	5E-04	0.193	ns	-0.001	0.001	0.314	ns
% Adults with Obesity	-0.005	0.001	5E-06	****	-0.003	0.002	0.047	*	-0.005	0.002	0.007	**
% Adults with Diabetes	0.011	0.004	0.0028	**	0.009	0.005	0.073	ns	0.008	0.005	0.142	ns
HIV Prevalence Rate	-8E-07	2E-05	0.958	ns	-5E-06	2E-05	0.752	ns	6E-06	4E-05	0.866	ns
% Smokers	0.013	0.002	1E-15	****	0.013	0.002	4E-07	****	0.009	0.002	4E-05	****
Segregation index	0.168	0.048	0.0005	***	0.138	0.061	0.0246	*	0.111	0.076	0.146	ns
% Rural	-4E-04	3E-04	0.175	ns	-0.001	5E-04	0.031	*	-4E-04	4E-04	0.265	ns
Median Household Income	5E-08	3E-07	0.852	ns	-8E-08	4E-07	0.820	ns	-1E-06	5E-07	0.0487	*
Education_age25	-0.002	0.001	0.0006	***	-0.001	0.001	0.468	ns	-0.003	0.001	0.0006	***
% Unemployed	0.009	0.002	5E-05	****	0.011	0.003	0.0004	***	0.010	0.003	0.0017	**
% Uninsured	0.001	0.001	0.659	ns	4E-04	0.002	0.834	ns	-0.001	0.002	0.548	ns
County_mrp_ideology	0.157	0.032	9E-07	****	0.122	0.048	0.0107	*	0.253	0.065	0.0001	***
	degrees of freedom: 565 R squared = 0.664				degrees of freedom: 242 R squared = 0.660				degrees of freedom: 295 R squared = 0.616			

Note. Weighted multivariate regression models are shown. Similar results were obtained when the regression models were unweighted (see Supplementary Figure 5).

https://doi.org/10.33774/apsa-2024-hf7gf **ORCID:** https://orcid.org/0000-0002-7221-5495

We found that the impact of higher communication about religion on COVID-19 mortality was primarily mediated in conservative-leaning counties, while in liberal counties discussions of religion did not predict mortality from COVID-19.

Discussions of vaccination had opposite predictive effects in liberal and conservative communities – more discussion of vaccination decreased mortality in liberal counties but increased mortality in conservative counties.

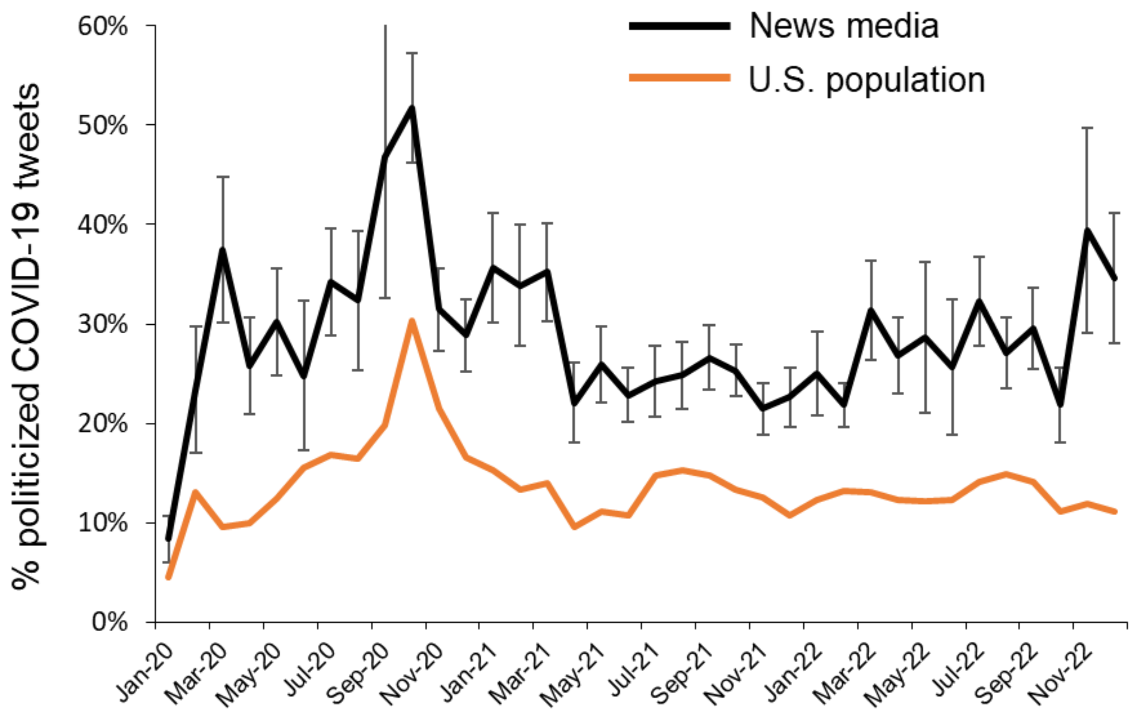
Discussions of mask-wearing and economic issues predicted lower mortality rates in liberal counties, but not conservative counties. And liberal counties where COVID-19 communication was more politicized were more likely to exhibit higher COVID-19 mortality rates.

Taken together, these results uncover specific vulnerabilities among U.S. counties that were conferred by their patterns of COVID-19 communication. They also identify possible protective effects of COVID-19 communication, suggesting that effective COVID-19 communication may save lives across U.S. communities.

The influence of news media and political elites on the COVID-19 communication of citizens

We next addressed RQ4 and asked whether the politicization of COVID-19 communication by the news media (Ye et al., 2021) may influence the COVID-19 communication of ordinary citizens. We analyzed the COVID-19 coverage on the Twitter accounts of five mainstream media channels during the first three years of the pandemic and compared the degree of COVID-19 politicization by news media vs. ordinary citizens. Figure 11 shows that, throughout the first three years of the pandemic, the news media coverage of COVID-19 was substantially more politicized than the communication of ordinary citizens. Interestingly, the evolution of politicized COVID-19 communication among citizens, though less pronounced, mirrored that of the media. This suggests that media coverage of COVID-19 may have contributed to the politicized content that was subsequently disseminated through the social networks of ordinary citizens.

Figure 11. U.S. news media politicized COVID-19 more than the general U.S. population



Note. Shown are mean ± S.E.M for five news media outlets (CNN, Fox News, MSNBC, NBC News and ABC News) (black) and the mean of 11,630 U.S. cities (orange).

Finally, we addressed RQ5 and explored the relevance of COVID-19 communication in a political context – during the 2022 midterm election season. We chose to focus on the 2022 midterm election season because our longitudinal analyses uncovered divergent patterns of COVID-19 communication across U.S. communities that persisted into late 2022.

We analyzed the communication of political candidates for the 2022 U.S. House of Representatives election during the two-month period prior to the election and found that Democratic candidates from reliably liberal districts were more likely to mention the COVID-19 pandemic in their pitches to potential voters (correlation between COVID-19 topic usage and the inverse of district ideology score, mrp – for liberal districts mrp<0, so the inverse of the mrp score was used in the correlation – Spearman r=0.313, $P=3x10^{-10}$). We also found that Republican candidates from the most conservative districts also tended to more often address COVID-19 in their communication with potential voters (correlation between COVID-19 topic usage and district ideology score, mrp – for conservative districts mrp>0 – Spearman r=0.113, P=0.029) (Table 2).

Table 2. Correlation between candidate's home district ideology and their COVID-19 communication on Twitter

Type of district	r	P value
Liberal-leaning districts*	r=0.313	$p=3\times10^{-10}$
Conservative-leaning districts	r=0.113	p=0.029

We then asked whether the effectiveness of Democratic and Republican candidates' COVID-19 communication predicted their chances of winning their election bids. For each candidate, the mean engagement (number of likes or retweets) of all COVID-19 related tweets posted in the two months prior to the election was divided by the mean engagement of *all* tweets posted by the candidate within the two-month period, to obtain a COVID-19 preferential engagement ratio (CPER). A CPER>1 indicates that a candidate's COVID-19 tweets were more engaging than the average tweet, whereas CPER<1 indicates that the candidate's COVID-19 tweets were less engaging than the candidate's average tweets. We then asked whether winning candidates were distinguished from losing candidates by their ability to craft effective messages related to COVID-19 policies and related issues.

We found that winning or losing Republican candidates could not be distinguished based on the effectiveness of their COVID-19 communication-related tweets (Table 3). This was also true among winning vs. losing Republican incumbents and challengers. By contrast, Democratic winners could be distinguished from losing candidates based on the effectiveness of their COVID-19 communication. Thus, losing candidates exhibited significantly more effective COVID-19 communication. This was true for all losing Democratic candidates compared to all winning Democrats, as well as for losing Democratic incumbents compared to incumbents who won their reelection bids (Table 3).

A qualitative analysis of the COVID-19-related tweets posted by losing Democratic candidates found that many of them prompted their audiences to get vaccinated or boosted, raised alarm about the continued seriousness of the disease, attacked their opponents for their role in crisis management, or criticized the Republicans for their policies or stances on pandemic management (Supplementary Table 1).

Table 3. COVID-19 preferential engagement ratios (CPER) for the audiences of political candidates during the 2022 midterm election season

		Won election		Lost election		
Type of engagement	**Group**	**CPER**	**S.E.M**	**CPER**	**S.E.M**	**P-value**
Tweet favorites	Republican candidates (all)	1.23	0.34	0.79	0.08	0.396
	Republican incumbents	1.31	0.39	N/A	N/A	N/A
	Republican challengers	0.69	0.15	0.8	0.08	0.51
	Democratic candidates (all)	**0.7**	**0.06**	**1.16**	**0.29**	**0.025***
	Democratic incumbents	**0.72**	**0.07**	**2.52**	**2.17**	**0.001****
	Democratic challengers	0.48	0.17	0.99	0.18	0.198
Retweets	Republican candidates (all)	1.29	0.29	0.96	0.11	0.485
	Republican incumbents	1.36	0.33	N/A	N/A	N/A
	Republican challengers	0.81	0.22	0.97	0.11	0.482
	Democratic candidates (all)	**0.74**	**0.06**	**1.19**	**0.3**	**0.027***
	Democratic incumbents	**0.76**	**0.06**	**1.89**	**1.53**	**0.006****
	Democratic challengers	0.5	0.21	1.09	0.27	0.325

Note. The data was obtained from 372 Republican candidates (213 won, 159 lost), 181 Republican incumbents (174 won, 7 lost) and 191 Republican challengers (39 lost, 152 won), as well as from 391 Democratic candidates (210 won, 181 lost), 186 Democratic incumbents (177 won, 9 lost) and 205 Democratic challengers (33 won, 172 lost). Note that none of the 7 Republican incumbents that lost their reelection bids posted any COVID-19 related tweets during the two-month period prior to the election (N/A). Two-tailed unpaired student's t-test was used to assess the statistical significance of CPER mean differences (P-values are indicated). SEM - Standard Error of the Mean

The fact that Democratic candidates who in late 2022 continued to address the pandemic, public health efforts and management efforts lost their election bids raises the possibility that Democratic audiences, and potentially Democratic voters, may have exhibited COVID-19 fatigue in late 2022, and Democratic candidates that effectively messaged about COVID-19 during that period may have been more likely to lose the election.

DISCUSSION

Polarized patterns of COVID-19 communication across the U.S.

Our research reveals robust and consistent geographical and temporal trends in COVID-19 communication within the United States, influenced significantly by both political beliefs and socio-economic circumstances. We observed a distinct polarization in COVID-19 discourse across the nation, primarily aligned with ideological divides. These findings suggest that social media networks, shaped by ideological, geographical, and cultural affiliations, may filter and steer COVID-19 discussions, leading individuals to encounter predominantly like-minded perspectives within their Twitter feeds. This concentration and direction of COVID-19 communication likely contributed to the emergence, propagation, and endurance of political polarization surrounding the pandemic.

Our analysis showed that users in the most liberal cities tended to talk less about mask-wearing throughout the pandemic – particularly between mid 2020 and early 2021 (Figure 3 and Supplementary Figure 2), and also engaged less with pro-masking tweets (Figure 8). The decreased communication about mask-wearing in liberal cities – which overall, exhibited higher rates of mask-wearing than conservative cities (Deane et al., 2021) – suggests that people who wore masks were less likely to discuss mask-wearing, and engage with others that discussed it, online. It may suggest that decreased communication about mask-wearing was a correlate of increased, not decreased, adherence to mask-wearing. The idea that more communication about mask-wearing by conservatives meant less adherence to mask-wearing rules is also consistent with a 2023 Pew Research Center survey which showed that “mask” was the most-frequent word Republicans used to describe their opinion towards the pandemic (Schaeffer, 2023). Moreover, most conservatives perceived mask-wearing as an institutional restriction, which limits their personal freedom (Aratani, 2020).

In contrast to communication about mask-wearing, users in more liberal cities posted more vaccination-related content in April-June 2021 – when the widespread Covid-19 vaccination was initiated (Supplementary Figure 3), and tended to engage more with other tweets about vaccination (Figure 8). Liberal cities had higher rates of vaccination than conservative cities (Funk, & Gramlich, 2021). This suggests that increased communication about vaccines and vaccination is a positive correlate of vaccination – in contrast to communication about mask-wearing, which appears to be a negative correlate of mask-wearing.

Users in the most liberal communities, unlike those in the most conservative communities, also tended to talk more about race and ethnicity and the economy. By contrast, users in the most conservative communities preferred to talk about religion, wearing a mask, and conspiracies, while tending to communicate less about social aspects and vaccination (Figure 3).

The tone of COVID-19 communication was also different in the most liberal and conservative communities. We found that the most liberal communities posted more positive messages throughout the pandemic (Supplementary Figure 4). By contrast, users in conservative communities, such as graying America, tended to post more negative COVID-19-related content during the second half of the pandemic (Figure 6). Thus, our analyses identifies communities whose attitudes may have been more positive, or negative, towards COVID-19.

Beyond differences along ideological lines, our study also uncovered robust differences between different types of American communities, along both cultural and socioeconomic lines. Thus, Graying America tweeted more about politics, used more divisive language in their posts, and discussed conspiracy theories, as were users in rural areas and Evangelical hubs (Figure 4). Graying America and Evangelical hubs also tended to be more negative towards COVID-19, especially starting in summer 2021 when the delta variant began spreading (Figure 6). Furthermore, communities that were more educated and affluent tweeted more pro-masking messages, discussed vaccination, education and social aspects, and used fewer foul words in their communication (Figure 7).

In sum, our survey reveals that COVID-19 communication patterns are sharply divided along ideological, cultural, and socioeconomic lines. This division not only underscores the deep-rooted disparities in how different communities perceive and respond to public health crises but also offers a unique lens through which to understand the complex interplay between political and social factors in shaping public discourse during the pandemic. These findings highlight the critical need for more nuanced and targeted communication strategies in addressing public health issues in a polarized society.

Local attitudes and patterns of vulnerability and resilience

To effectively manage a public health crisis, local and national leaders must be aware of citizens' attitudes throughout the crisis to identify areas of vulnerability. One major source of information about public opinion are polls and surveys. These polls have provided important insights into the public's attitudes, beliefs and behaviors during the

COVID-19 pandemic. In March 2020, at the beginning of the pandemic, Pew Research Center's first survey on COVID-19 found that the majority of the public (70%) perceived the novel coronavirus as a threat to the economy, while less than 50% thought it was a major public health threat. In addition, a majority of the sample, particularly Republicans, said that the media exaggerated the risk of the virus. In the second year of the pandemic, a majority of Democrats and Republicans still agreed that the pandemic was a threat to the economy. While most partisans approved the work of their local medical professionals, their opinions diverged sharply when evaluating elected officials, with differences widening from local to national levels. At the local level, 60% of Democrats felt their local elected officials handled the pandemic responses well, compared to 48% of Republicans. Nationally, 79% of Democrats approved of Joe Biden's pandemic response, while only 20% of Republicans agreed. Conversely, 71% of Republicans felt Donald Trump managed the pandemic effectively, in contrast to just 7% of Democrats who shared that view (Schaeffer, 2021). Thus, the public became sharply divided, along ideological lines, in their assessment of political leaders.

The Americans' views on health restrictions diverged, along ideological lines from 2020 to 2021. Thus, in 2020, Republicans and Democrats largely agreed on public health restrictions, such as restricting international travel (96% of Republicans vs. 94% of Democrats), avoiding gatherings (82% vs. 92%), imposing restaurant restrictions (78% vs. 91%), and closing in-person learning for K-12 schools (85% vs. 94%). However, in 2021, support for public health measures became polarized, especially for restrictions on group gatherings (56% of Republicans vs. 93% of Democrats agreed), restaurant restrictions (23% vs. 74%), and in-person learning for K-12 (25% vs. 66%).

By the end of 2022, an Ipsos (2022) survey found just over a third of Americans viewed the coronavirus as a severe or moderate risk. Partisan differences still persisted, and views diverged significantly on key issues such as the effectiveness of COVID-19 vaccines, pending on COVID-19-related public health efforts, and Dr. Anthony Fauci's role.

Our findings were in agreement with the findings of these surveys, and identified differences between the communication patterns of liberal and conservative communities (see above). However, our longitudinal (over a three-year period) and granular (analysis of thousands of communities) survey collected real-world communication of a much larger sample of Americans (hundreds of thousands) across America. As such, our findings provide a more granular and temporally-adjusted look at people's communication, and may shed light into people's attitudes and behaviors. Thus, our analysis uncovered specific aspects of COVID-19 discourse that correlated with higher COVID-19 mortality rates when prevalent among community members. The

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use of politicized and conspiratorial language emerged as predictive factors for increased mortality rates. Particularly harmful, even fatal, were conspiracies surrounding COVID-19, as they fostered distrust in the scientific and medical communities combating the virus. Many of these conspiracies aimed to discredit the existence of the coronavirus, labeling it as a hoax orchestrated by billionaires or foreign governments, thereby undermining the authority, efforts, and intentions of public health and government officials in the United States.

Our analysis also found that communicating about COVID-19 in religious terms was linked with higher mortality rates in U.S. communities. Because our study uncovered correlations, not causation, it is possible that communities that experienced high death rates were more likely to invoke religious themes in their communication. It is equally possible that religious themes may have been invoked to argue that people should congregate and socialize, which may have facilitated the spread of the virus. Thus, the involvement of religious beliefs and their role in COVID-19 communication may be more complex and require further investigation. Notably, previous scholarly work has proposed that religiosity plays a significant role in shaping widespread polarization. For instance, (Carothers & O'Donohue, 2019) contend that ideological divisions in the United States have deep-seated historical and cultural origins, rendering the nation distinct from others due to the pronounced intertwining of political ideology, religion, and ethnicity among various communities. This phenomenon, often referred to as the 'iron triangle' within the U.S. context, has led to a correlation where individuals adhering to conservative political beliefs are more commonly white and religious. Conversely, those aligned with liberal political views tend to exhibit greater racial diversity and lower levels of religious affiliation. Therefore, building upon the perspectives outlined by Carothers and O'Donohue (2019) and Kerr et al. (2021), we suggest that religion becomes a significant factor in the dynamics of mass polarization amid the pandemic, potentially exerting a disproportionate influence within conservative communities.

Our analysis also uncovered evidence of apathy and fatigue across U.S. communities. Thus, during the latter stages of the pandemic, certain conservative communities, such as Graying America, Evangelical hubs, or working-class rural areas, exhibited a more negative discourse surrounding COVID-19.

Among liberal communities, our analysis uncovered evidence of COVID-19 fatigue. Thus, liberal communities were less inclined to discuss topics like mask-wearing, and were much less engaged by pro-masking messages. Additionally, Democratic politicians running for office were more likely to lose the election if they had been particularly effective in their COVID-19 communication efforts (Table 3).

We argue that the COVID-19 fatigue may have resulted from the combined effects of psychological trauma stemming from the loss of over a million American lives, millions hospitalized, job losses, housing instability, and disruptions to daily life such as social activities, schooling, and travel. Such fatigue and trauma may have contributed to a profound skepticism towards institutions, potentially extending to skepticism of political elites. Another contributor to this fatigue may have been the saturating media coverage of COVID-19 and the stark politicization of COVID-19 by the media (Figure 11) and possibly by politicians (Table 2 and Supplementary Table 1). Indeed, the public was less interested in political aspects of the pandemic (Figure 11) and was, overall, more focused on social aspects, healthcare, and preventative measures (Figure 1).

A March 24 article in The New York Times cited Ryan Hagen, who oversees an oral history project on the pandemic at Columbia University, noting the difficulty in sustaining participants' engagement as the crisis waned. The article also quoted Eric Klinenberg, a sociology professor at New York University, who described the enduring impact of the pandemic as a social ailment in his book, "2020: One City, Seven People, and the Year Everything Changed." Additionally, a nonpartisan team of over 30 experts, known as the Covid Crisis Group, conducted an analysis and published the book "Lessons from the Covid War," suggesting that the federal government's communication failures may have hastened distrust in institutions. Considering our analysis indicating that Democratic politicians that continued to address COVID-19 in fall 2022 were more likely to lose their election (Table 3), we posit that COVID-19 fatigue may have also fostered skepticism towards political elites who persisted in addressing the pandemic despite voter fatigue.

Drawing from our observations, we contend that understanding and anticipating variances and inconsistencies in COVID-19 communication among citizens is vital for communication specialists. This comprehension is crucial for developing more efficient strategies to engage the entire public in adopting preventive COVID-19 measures. Additionally, we assert that it is imperative for political leaders to grasp the mood of the populace during an extended pandemic. This understanding enables the implementation of policies that are finely tuned to the needs of local communities, considering their socio-economic and ideological compositions. Such awareness is equally pertinent to their prospects for re-election and may, in a broader sense, influence the makeup and efficacy of government operations.

Toward a computation-based approach to crisis management

A study conducted by Nielsen, et al. (2020) assessed how citizens from six countries (Argentina, Germany, South Korea, Spain, United Kingdom and the U.S.) accessed and evaluated information about the coronavirus and public health efforts. Encouragingly, the authors found that all surveyed demographics had similar attitudes to the usefulness and reliability of social media and other online information sources about the pandemic.

Despite that, Lin (2020) has observed that social media is characterized by a conflict between users who accept and those who doubt the medical and scientific facts about COVID-19 and the usefulness of public health guidelines. This conflict could then fuel mass polarization but also the amplification of distrust in science and misinformation (Lin, 2020; Ajekwe, 2022). One potential risk of a conflict between those who accept and those who reject evidence-based information on social media is that those that reject evidence-based claims may be more prone by influence by opinion leaders (e.g. such as politicians, religious figures, celebrities or influencers) and may adopt attitudes, beliefs and behaviors that may be harmful to their own health and that of their local communities (Ajekwe, 2022).

As discussed by Aiyewumi and Okeke (2020), during public health emergencies, such as the COVID-19 pandemic, accurate information and reliable communications are critical to identifying deficiencies and vulnerabilities, devising policies, and directing resources. The authors have highlighted the importance of information specialists and technologists who can collect, analyze and interpret the vast amounts of COVID-19-related information that has been generated during the pandemic, and who can then relay their expert assessment to other stakeholders.

Our local analysis of COVID-19 communication throughout the pandemic has uncovered several vulnerabilities, as well as aspects of resilience, that may inform current and future efforts to integrate large-scale computational analyses and surveys into disease management and policy making. We uncovered several areas of COVID-19 communication that were divergent between liberal-leaning and conservative-leaning communities. One such area was COVID-19-related disinformation about vaccination that was spread in some conservative communities and which predicted higher COVID-19 mortality rates. A second area was religion and the communication of religious messages linked to COVID-19, which also predicted higher mortality in conservative communities, but not liberal communities. Similarly, in liberal communities, higher politicization of COVID-19 may confer vulnerability, leading to higher mortality rates. to On the other hand, more sustained messaging about mask-wearing and the benefits of vaccination, observed in liberal communities, predicted lower mortality rates, and may be indicative of

https://doi.org/10.33774/apsa-2024-hf7gf ORCID: https://orcid.org/0000-0002-7221-5495

local resilience during the pandemic. Our survey also identified differences in communication that may have been caused by social cleavages other than ideology. Thus, we noted stark differences between the communication patterns of the 16 types of American communities, raising the possibility that the COVID-19 crisis may not only fueled mass ideological and affective polarization, but also polarization along other lines – such as for example, economic (rich vs. poor communities), geographical (rural vs. urban communities) or religious (religious vs. secular communities). Thus, further, in-depth, analysis of our dataset may uncover additional patterns of mass polarization and local vulnerability during the COVID-19 pandemic.

Limitations and future directions

Given Twitter restrictions, our dataset only supports inferences at the city and county levels. Future studies could attempt to acquire (and in some cases, purchase) larger datasets and conduct a more granular analysis than the analysis presented here. They could also attempt to collect more extensive information about *individual* Twitter users – for example, by collecting a representative sample of all their communications, which could be used to computationally infer a user's ideology or attitudes toward specific issues. Nevertheless, our analysis demonstrates the emergence of robust geographical, ideological, and socioeconomic patterns of COVID-19 communication during the pandemic in the U.S., and identifies polarizing patterns of communication that may have conferred vulnerability, or resilience, during the pandemic – and, may also have had political and electoral implications. Our findings highlight the need for a better understanding of citizens' communication during public health crises, which may not only provide a better understanding of citizen's behavior – from complying or resisting public health guidelines to mass polarization – but may also inform policy decisions and efforts to manage future health emergencies and crises.

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CONFLICT OF INTEREST

The authors declare no ethical issues or conflicts of interest in this research.

ETHICAL STANDARDS

The authors affirm that this article adheres to the APSA's Principles and Guidance on Human Subject Research.

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Supplementary Figure 1. The political ideology of U.S. communities predicts their COVID-19 topic usage and sentiment on Twitter

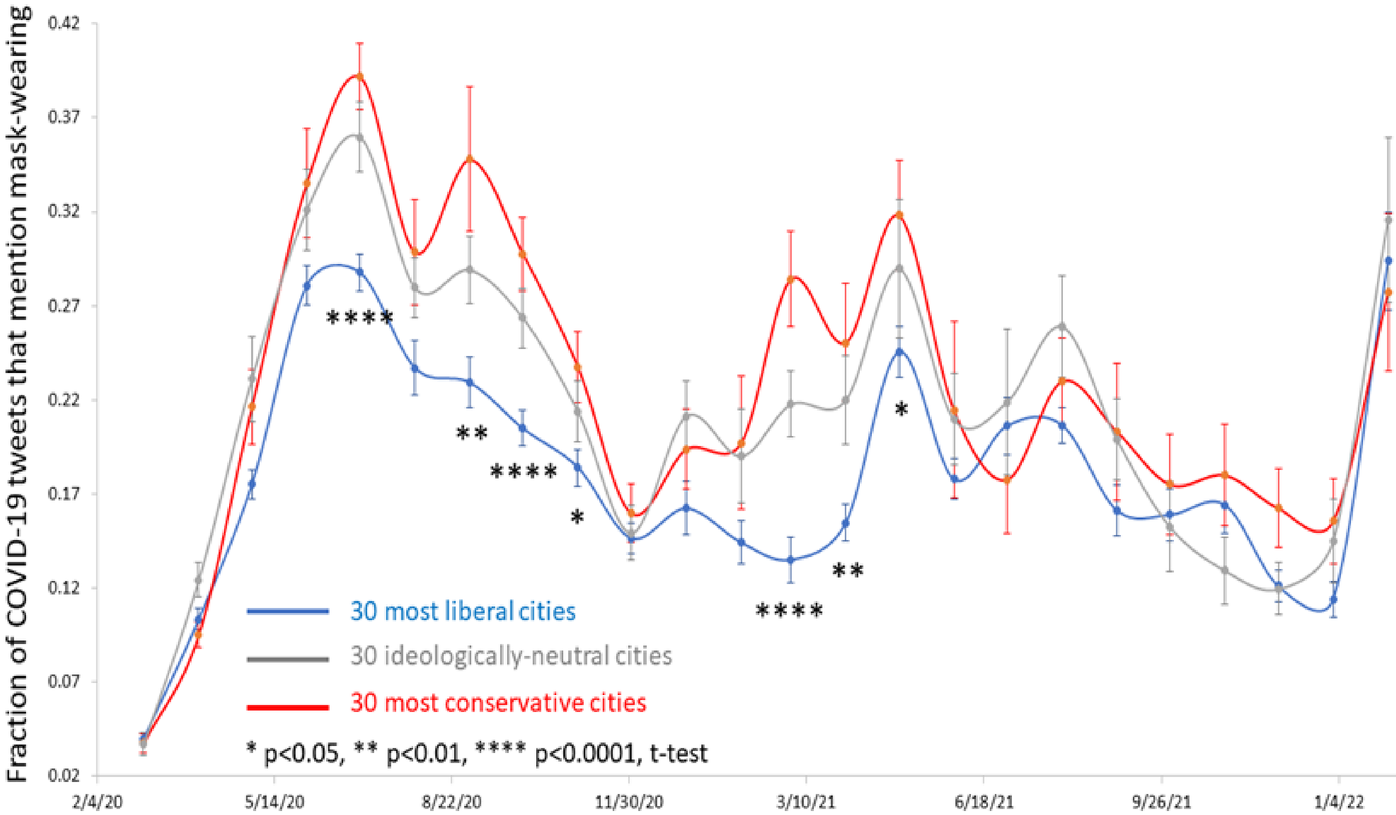
Correlation between county ideology and COVID-19 communication topic usage									
	All counties			Liberal* (-mrp>0)			Conservative (mrp>0)		
COVID-19 communication	r	P value	Sig	r	P value	Sig	r	P value	Sig
Masking (all)	0.090	0.0028	**	-0.339	2E-10	****	-0.021	0.57	ns
Pro-masking	-0.163	4E-08	****	0.035	0.52	ns	-0.091	0.011	*
Vaccination	-0.177	3E-09	****	0.106	0.053	ns	-0.093	0.0096	**
Healthcare, public health	0.025	0.40	ns	0.014	0.80	ns	0.016	0.65	ns
Social aspects	-0.168	2E-08	****	0.092	0.093	ns	-0.121	0.0007	***
Economy	-0.136	5E-06	****	0.145	0.008	**	-0.069	0.054	ns
Religion	0.192	1E-10	****	-0.128	0.019	*	0.114	0.001	**
Race, ethnicity	-0.228	1E-14	****	0.372	2E-12	****	-0.098	0.006	**
Education	0.056	0.060	ns	-0.143	0.009	**	-0.002	0.96	ns
Politics	-0.128	2E-05	****	-0.001	0.98	ns	-0.108	0.002	**
Partisan, divisive language	-0.105	0.0004	***	0.045	0.42	ns	-0.091	0.011	*
Conspiracies	0.074	0.013	*	-0.065	0.24	ns	0.069	0.054	ns
Foul words	-0.082	0.006	**	-0.163	0.003	**	-0.089	0.012	*
Mean sentiment of tweets	-0.059	0.049	*	0.034	0.53	ns	-0.040	0.27	ns

Correlation between city ideology and COVID-19 communication topic usage									
	All cities			Liberal* (-mrp>0)			Conservative (mrp>0)		
COVID-19 communication	r	P value	Sig	r	P value	Sig	r	P value	Sig
Masking (all)	0.151	P<10-15	****	-0.132	5E-09	****	-0.005	0.86	ns
Pro-masking	-0.047	0.009	**	0.019	0.41	ns	-0.053	0.0699	ns
Vaccination	-0.067	0.0002	***	0.009	0.69	ns	-0.034	0.24	ns
Healthcare, public health	0.024	0.18	ns	-0.031	0.18	ns	0.033	0.26	ns
Social aspects	-0.050	0.0054	**	0.034	0.14	ns	-0.077	0.009	**
Economy	-0.064	0.0003	***	0.026	0.26	ns	-0.087	0.003	**
Religion	0.169	P<10-15	****	-0.123	5E-08	****	0.081	0.006	**
Race, ethnicity	-0.185	P<10-15	****	0.160	1E-12	****	-0.053	0.068	ns
Education	0.099	3E-08	****	-0.011	0.62	ns	0.018	0.54	ns
Politics	-0.014	0.44	ns	-0.038	0.090	ns	-0.051	0.083	ns
Partisan, divisive language	-0.004	0.84	ns	-0.028	0.22	ns	-0.047	0.11	ns
Conspiracies	0.060	0.0008	***	-0.053	0.0197	*	0.033	0.25	ns
Foul words	-0.046	0.0097	**	-0.051	0.023	*	-0.092	0.0016	**
Mean sentiment of tweets	-0.030	0.089	ns	0.054	0.0168	*	-0.019	0.52	ns

Note. Shown are the Spearman correlation coefficients (r) between the mrp scores of U.S. counties (top) or cities (bottom) and the COVID-19 topic usage on Twitter by users located in each county or city, between late January 2020 and December 31, 2022. Counties and cities for which at least 100 tweets were collected were included in the analysis.

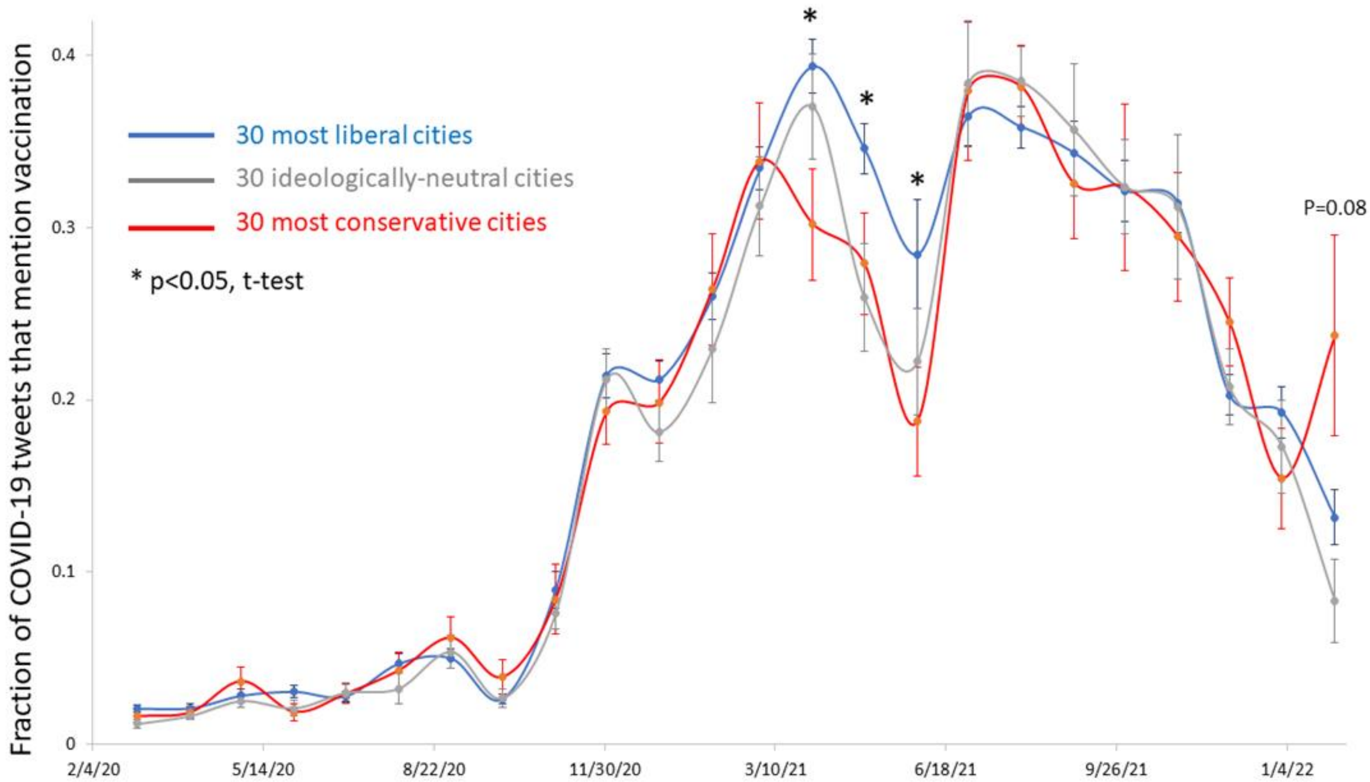
* a negative mrp score (-mrp) was used in correlations for liberal counties or cities only, to assess correlations between increasing liberal ideology and COVID-19 topic usage.

Supplementary Figure 2. Twitter communication about mask-wearing



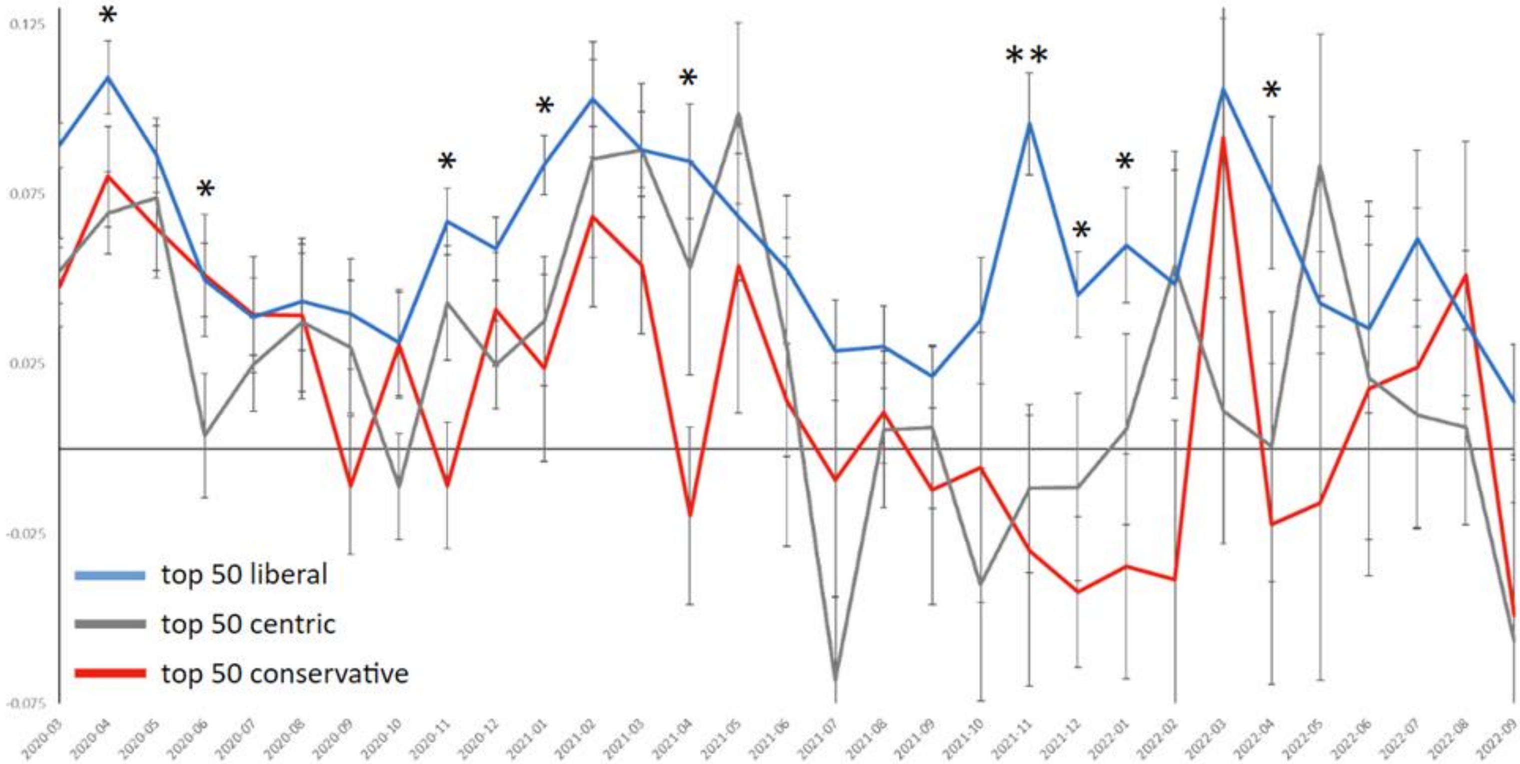
Note. The blue, red, and grey lines represent the monthly average ± S.E.M. (standard error of mean) of masking-related tweets by users from the top 30 most liberal and conservative cities, as well as 30 most centric (mrp score ~0) cities, respectively.

Supplementary Figure 3. Twitter communication about COVID-19 vaccination



Note. The blue, red, and grey lines represent the monthly average ± S.E.M. (standard error of mean) of COVID-19 vaccination-related tweets by users from the top 30 most liberal and conservative cities, as well as 30 most centric (mrp score ~0) cities, respectively.

Supplementary Figure 4. Tweet sentiment during the COVID-19 pandemic



Note. The blue, red, and grey lines represent the monthly average ± S.E.M. (standard error of mean) of tweet sentiment for users from the top 50 most liberal and conservative cities, as well as 30 most centric (mrp score ~0) cities, respectively. * p<0.05, two-tailed, unpaired t-test.

Supplementary Figure 5. COVID-19 Twitter communication predicts COVID-19 mortality in U.S. counties

	All counties				Counties with mrp<0				Counties with mrp>0			
Variable	**Estimate**	**SE**	**P value**	**Sig**	**Estimate**	**SE**	**P value**	**Sig**	**Estimate**	**SE**	**P value**	**Sig**
Intercept	0.171	0.093	0.066	ns	0.000	0.134	0.998	ns	0.410	0.137	0.0030	**
Masking (all)	-0.137	0.089	0.126	ns	**-0.388**	**0.184**	**0.0361**	*	-0.043	0.111	0.700	ns
Pro-masking	0.189	0.286	0.508	ns	0.151	0.485	0.756	ns	0.352	0.358	0.326	ns
Vaccination	0.114	0.123	0.355	ns	**-0.439**	**0.185**	**0.0182**	*	**0.423**	**0.165**	**0.011**	*
Healthcare, public health	-0.100	0.082	0.224	ns	-0.079	0.103	0.440	ns	-0.128	0.128	0.317	ns
Social issues	0.102	0.108	0.344	ns	0.170	0.177	0.336	ns	0.241	0.144	0.095	ns
Economy	-0.472	0.247	0.056	ns	**-0.884**	**0.358**	**0.0142**	*	-0.424	0.332	0.202	ns
Religion	**1.555**	**0.579**	**0.0075**	**	0.673	1.089	0.537	ns	**1.464**	**0.738**	**0.048**	*
Race, ethnicity	-0.842	0.633	0.184	ns	-0.519	0.814	0.525	ns	-1.598	0.934	0.088	ns
Education	0.023	0.245	0.924	ns	-0.177	0.305	0.563	ns	0.059	0.390	0.880	ns
Politics	0.169	0.087	0.052	ns	**0.373**	**0.144**	**0.00995**	**	0.186	0.112	0.098	ns
Partisan, divisive language	-0.582	0.502	0.247	ns	-1.014	0.816	0.215	ns	-0.494	0.636	0.438	ns
Conspiracies	**1.013**	**0.427**	**0.018**	*	0.800	0.709	0.260	ns	0.636	0.539	0.239	ns
Foul words	-0.281	0.201	0.162	ns	0.065	0.370	0.861	ns	-0.152	0.249	0.543	ns
Mean tweet sentiment	**-0.335**	**0.111**	**0.0028**	**	-0.308	0.171	0.073	ns	-0.269	0.155	0.084	ns
COVID-19 cases (%)	0.0019	0.0007	0.005	**	0.0034	0.0008	7E-05	****	-3.2E-04	0.0011	0.765	ns
COVID-19 vaccination (%)	3.0E-05	0.0004	0.943	ns	6.8E-04	0.0005	0.171	ns	-0.001	0.0007	0.228	ns
% Adults with Obesity	-0.006	0.0012	8.5E-07	****	-0.0036	0.0017	0.0288	*	-0.006	0.0018	0.0013	**
% Adults with Diabetes	0.010	0.0037	0.0054	**	0.0094	0.0051	0.0695	ns	0.008	0.0055	0.148	ns
HIV Prevalence Rate	-1.5E-06	0.0000	0.927	ns	-3.84E-06	1.7E-05	0.823	ns	-1.3E-05	3.7E-05	0.730	ns
% Smokers	0.0121	0.0016	2.4E-13	****	0.0131	0.0024	7E-08	****	0.008	0.0023	0.00041	***
Segregation index	0.181	0.0477	0.0002	***	0.152	0.0594	0.011	*	0.106	0.0742	0.156	ns
% Rural	-0.0004	0.0003	0.193	ns	-0.0008	0.0005	0.0897	ns	-5.9E-04	0.0004	0.136	ns
Median Household Income	-1.1E-07	0.0000	0.735	ns	1.103E-07	3.8E-07	0.771	ns	-1.6E-06	5.5E-07	0.0049	**
Education_age25	-0.0025	0.0006	0.0001	***	-0.001028	0.0008	0.210	ns	-0.003	0.0010	0.0017	**
% Unemployed	0.009	0.0021	5.5E-05	****	0.0096	0.0029	9E-04	***	0.010	0.0031	0.0013	**
% Uninsured	0.0013	0.0012	0.313	ns	0.00095	0.0017	0.587	ns	1.3E-04	0.0018	0.943	ns
County_mrp_ideology	0.166	0.0345	1.8E-06	****	0.111	0.0524	0.0357	*	0.243	0.0656	0.0003	***
	degrees of freedom: 565 R squared = 0.634				degrees of freedom: 242 R squared = 0.653				degrees of freedom: 295 R squared = 0.579			

Note. Unweighted multivariate regression models are shown.

Supplementary Table 1. Examples of COVID-19-related tweets posted during the two-month period prior to the election by Democratic candidates who ultimately lost their election bids.

Name	Date	Text
Carolyn B. Maloney	2022-09-16	ATTN NYers: The new #COVID19 booster is now available. Everyone should vaxx up to prepare for the winter when more people are indoors and viruses spread more easily.
Jackie Speier	2022-09-16	Great news CA, COVID-19 boosters are ready! is here to help you find a vaccine. Check-out their website to schedule an appointment or find a walk-in clinic. Keep yourself and your loved ones safe this fall & get boosted!
Rep. Cindy Axne	2022-09-22	Don't forget: The latest COVID-19 vaccine boosters are now available across our state. Find an appointment near you at #IA03
Carolyn B. Maloney	2022-10-06	Winter health update: With the cooler winter months upon us and more NYers spending time indoors, I encourage EVERYONE to get the updated COVID-19 booster and a flu shot. Find an appointment here for both:
Dianne Dodson Black	2022-09-15	Mississippi, mismanaged and leading us to ruin. Highest COVID per capita in the nation. Lowest life expectancy. Highest infant mortality rate. Highest gun death. Poorest in nation. Shower with mouths closed. Republicans don't care.
Dr. Cindy Banyai	2022-09-18	Dr. Cindy Banyai talked about the seriousness of the Delta #COVID19 variant in this episode of Perspective on Lee Pitts Live. #OurHealth
Bethany Mann	2022-09-22	Today, I protected myself, my family, and my community by getting my flu shot and the bivalent COVID-19 booster. I am immensely thankful for the scientists and researchers who put in long hours in the lab to save people from preventable death and illness
Dick Ausman	2022-09-24	Over one million Americans –15,000 in WI and 2200 in CD7– have died from Covid 19, including hundreds of thousands who could have been saved if not for the corrupt mishandling of the pandemic, aided and abetted by Tiffany. Tiffany wants us to forget, but we can’t and won’t.
Marisa Wood	2022-09-26	The pandemic was a trying time for everyone. As a teacher, I feel attacked and disrespected by words. What he calls 'collusion', I call safety precaution, so are youngest and most vulnerable are safe along with my fellow teachers and school staff.
Kathleen Brown	2022-09-27	Please take a couple of minutes to watch. We are in the fight of our lives as a nation. My opponent is an election denying, COVID denying, FBI agent attacker who want women across the nation to be stripped of all bodily autonomy. He wants to silence
Dick Ausman	2022-10-04	With WI reeling from Covid, Tom Tiffany voted against money for extending weekly unemployment benefits, stimulus checks, child tax credits, mortgage and homeowner assistance, and other relief for the homeless. He doesn’t care about his constituents, and that isn’t changing.
Dick Ausman	2022-10-12	Tom Tiffany’s legacy: 15,000 in Wisconsin dead from Covid, 2,200 in Congressional District 7. Don’t let him try to spin this tragedy. He boosted the calculated lies of the administration. The blood’s on his hands.
Cinde Wirth	2022-10-17	💉💉 Bivalent COVID Booster shot and Flu shot— ✅ Take care of yourself- We aren’t quite through this yet. Two women saw my shirt & told me they loved it. One was getting her shot and going to vote 💪🗳️ #RoeYourVote #Roevember #VoteWirth #FirePence

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Kyle Parrish	2022-10-19	So, my memory fails me. When are all of us that got the COVID vaccine supposed to die some kind of horrible death? And shouldn't I be getting better Internet with this chip that they put inside me? Just wondering. #ncpol #antivaxxers #AntiVaccine #COVIDisAirborne
Mary Brannon	2022-10-22	GOP Reps Refused to Wear Masks During Capitol Lockdown via Do not vote for Markwayne Mullin. Vote Blue in 2022, Democracy and not being embarrassed by Jethro Mullin depends on it. Share- Vote Kendra Horn!
Robin Fulford	2022-10-26	Dr Fauci is out here trying to save the lives of the people who love to hate him. The rest of us are vaccinated or can't be. #FauciOuchie #GetVaccinated
Conor Halbleib	2022-11-01	I always thought it was weird when the anti-vaxxers call getting a medical shot a "jab." They really treat getting a routine shot like a toddler does. I can handle it fine, but if it makes them feel better, we can give them a lollipop and tell them they are so brave afterwards.
Kyle Parrish	2022-11-03	Get vaxxed!