Original Paper

Search Interest in Alleged COVID-19 Treatments During the Pandemic and the Impact of Mass News Media Coverage Based on Google Trends and Media Cloud Data: Retrospective Analysis

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Abstract

Background: During a public health emergency, interest in unsafe or illegitimate medications can delay appropriate treatment and foster medical mistrust.

Objective: The aim of this study is to assess the relationship between search interest and media coverage of 3 purported COVID-19 treatments: hydroxychloroquine, ivermectin, and remdesivir.

Methods: The authors obtained daily US-based Google Trends and Media Cloud data from 2019 through 2022, conducted national-level anomaly detection, and assessed the state-level association of treatment-specific search interest and media coverage by regressing search interest against daily media coverage, and vice versa, for each treatment using a 2-stage process. This allowed us to explicitly model the questions: (1) does a state have any of the outcomes (search interest or media coverage), and (2) given a nonzero outcome, how much is it impacted by the exposure?

Results: Search interest and media coverage of all 3 treatments were significantly elevated during the study period. Anomaly detection identified several periods of higher-than-expected activity; anomalies in search interest and media coverage showed similar temporal patterns within treatments. There were distinct patterns of media source bias across treatments: while the plurality of top sources for all treatments were rated “Left” or “Left Leaning,” ivermectin was covered by the highest number of “Right”-biased sources, and remdesivir had the highest coverage by “Center” or unbiased sources. Significant associations between media coverage and search interest were observed for all 3 treatments. Media coverage had the strongest impact on same-day search interest for hydroxychloroquine (21.3% increase, 95% CI 20.1%-22.5%) and ivermectin (18.3% increase, 95% CI 16.8%-19.7%), and a more modest impact for remdesivir (12.8% increase, 95% CI 11.8%-13.8%). For hydroxychloroquine and remdesivir, this same-day effect was more transient, while interest in ivermectin remained elevated at a comparable level 1 and 2 days after media coverage. When evaluating the separate impact of search interest on media coverage, the associations were much weaker for all 3 treatments and all lagged conditions.

Conclusions: During a public health emergency, the information accessed by populations can directly influence health-seeking behaviors, potentially resulting in life-threatening consequences. Given the observed associations between treatment-related news media coverage and public interest in those treatments, our results suggest that news media serve as a powerful mechanism for experts to inform the landscape of public opinion and to reach audiences during future public health emergencies.

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Introduction

Throughout the early COVID-19 pandemic, several repurposed drugs were evaluated as potential COVID-19 treatments in the United States, including hydroxychloroquine, ivermectin, and remdesivir. Hydroxychloroquine, an antimalarial and antirheumatic drug, received an emergency use authorization from the US Food and Drug Administration (FDA) to treat hospitalized patients with severe COVID-19 in March 2020, but this was soon revoked after clinical trials showed harmful cardiovascular side effects at the doses being dispensed [1]. Ivermectin, an antihelminthic, was proposed as an antiviral agent for COVID-19 in early 2020, leading to the initiation of several randomized controlled trials between mid-2020 and 2021 [2]; however, results were generally inconsistent and inconclusive, leading the FDA, the US National Institutes of Health, and the World Health Organization to recommend against its use in 2021 [3]. Remdesivir, an antiviral originally developed to treat hepatitis C, was approved by the FDA for persons hospitalized with COVID-19 in October 2020 after multiple clinical trials showed moderately improved outcomes among hospitalized cases [4]. Public interest in these treatments varied over time, driven partially by governmental, political, and media responses to current events [5]. For hydroxychloroquine and then ivermectin, public demand for the drugs caused international pharmacy shortages, and in the case of ivermectin—a drug commonly used for livestock deworming—shortages of veterinary ivermectin as well [6,7]. Beyond causing shortages, public interest in unsafe or untested or off-label medications during a public health emergency can delay access to appropriate treatments and foster mistrust in the medical system, a detriment at both individual and population levels. Therefore, both for situational awareness and interventional purposes, it is critical for health and policy communities to understand how the public obtains medical information during an emerging crisis.

One method of evaluating public interest in medical information is the use of internet search data. These data can serve as a large-scale, near real-time proxy for public interest by providing insight into what information people seek online, including the subject, timing, and frequency of specific topics. A recent study in Switzerland found that 55% of Google searches were informational (as opposed to transactional or navigational) [8], and in 2019, roughly 7% of Google searches (about 1 billion searches daily) were related to health [9]. This makes internet search data—publicly available through Google Trends (GT)—an attractive tool for health information research [10]; indeed, GT was used extensively throughout the pandemic to measure population engagement with public health messaging on topics like masking, vaccines, and misinformation, as well as interest in COVID-19 more broadly [11,12].

Another way to gauge public interest in a topic is by assessing relevant news media coverage—a data source that is particularly useful for topics such as uncommon medications, which would rarely enter the public zeitgeist otherwise. The impact of news media on public interest and changing health behaviors has been well studied [13,14], including during the COVID-19 era [7,11,15]. Previous research by our team and others has assessed a variety of health-related topics and their relationship with news media coverage using services like Media Cloud (MC) [16], an open-source content analysis tool that collects time series of national and subnational news media coverage, comprising data from more than 50,000 news sources since its inception. The bulk of MC's corpora comprises news stories from web-based media sites, which is particularly relevant, as 86% of US adults reported getting news from an online source in 2023 [17].

Interestingly, the relationship between public interest and media coverage is not unidirectional; studies in communication theory demonstrate that the media can also serve as a reflection of public opinion rather than functioning solely as its driver—a phenomenon known as the "reflection hypothesis." [18] As interest in a topic increases, people begin searching for things they see in the news, while in response, the news covers things it knows people are interested in [19].

Our study investigated the possibility of bidirectional relationships between online search interest and media coverage to evaluate exposure to and access to health-related information during the COVID-19 pandemic. Specifically, we examined (1) the extent to which US news sources covered supposed COVID-19 treatments, (2) the extent of public interest in these treatments, as reflected by online search interest, and (3) the relationship between these data sources within the United States.

Methods

Data Sources for News Media and Internet Searches

We used 2 primary data sources to assess the relationship between treatment-related news media coverage and treatment-related search interest in the United States: MC and GT. All data were obtained for the period from January 2019 through December 2022 using the queries "hydroxychloroquine," "ivermectin," and "remdesivir" for both MC and GT (more details on how data were obtained can be found in the Supplemental Methods in Multimedia Appendix 1). Data from 2019 were included in the analysis to provide a prepandemic baseline for each of these search terms; data collection ceased in 2022 after a sustained period of low search interest and media coverage of all 3 terms.

Daily treatment-related news media coverage data were downloaded from MC's national- and state-level news corpora. This was done by visiting the Media Cloud website [16], creating a free account, logging in, and entering a keyword, such as "ivermectin." We used the Boolean "ANY" to match any phrase including a treatment name in the headline. A custom time frame from January 1, 2019, through December 31, 2022, was applied. We restricted the analysis to single-word treatment keywords. In MC, one-word queries return any media containing that word anywhere in the content. News corpora include media articles published in either national (eg, Reuters) or state-specific news sources (eg, Arkansas Times) and report the daily normalized content percentage (ie, the number of corpus-specific articles reporting on a topic of interest on a given day divided by the total number of corpus-specific articles on the same day).

Daily treatment-specific Google search interest data were downloaded using the GT dashboard at both the national level and, separately, the state level. This was done by visiting the GT website [10], entering a keyword, such as "ivermectin," and clicking "Explore." A custom time frame from January 1, 2019, through December 31, 2022, was applied. We restricted the analysis to single-word treatment keywords. When a search term is entered into GT, the platform returns data for all searches that include that word, not only exact matches. Thus, querying "ivermectin" captures search interest from all queries containing that string, including contextual phrases such as "ivermectin covid," "ivermectin dose," and "ivermectin treatment," without requiring these to be specified individually. As a result, our single-term queries do not restrict the data to exact-match searches and are unlikely to underestimate aggregate search interest. Although misspellings and variant spellings are not directly captured by our methodology, the use of a search *topic* rather than a search *term* enables retrieval of all related terms, including misspellings. When comparing interest over time across the 3 treatment terms and topics, the patterns were incredibly similar, and thus we retained only results from our original term query.

GT returns a normalized index of relative search interest scaled from 0 to 100, where 100 represents the peak search volume within the queried window. Because daily observations are only available for query windows of approximately 9 months or less, and because each query is independently normalized to its own within-window maximum, a 2-pass extraction procedure was used to obtain a consistent daily series across the full study period. In the first pass, the 4-year window was divided into 9 contiguous approximately 6-month subwindows, and daily data were retrieved for each term-geography-subwindow combination (1377 queries). Each resulting series was internally consistent but expressed on its own local 0 to 100 scale, with 100 anchored to the highest-search day within that subwindow. In the second pass, a single 4-year query was issued for each term-geography cell (153 queries), returning weekly observations on a common 0 to 100 scale anchored to that cell's 4-year peak. Daily subwindow series were then rescaled using min-max rescaling, mapping each subwindow's local minimum and maximum onto the corresponding values from the 4-year reference series, preserving day-to-day variation while reexpressing each subwindow on a common scale. Rescaled subwindows were concatenated to produce 153 daily series of 1461 observations each.

National-Level Anomaly Detection in Treatment-Specific Search Interest and Media Coverage

To identify peaks in treatment-related search interest and media coverage, we performed anomaly detection for each treatment in the respective time series at the national level using the a*nomalize* package in R (R Foundation for Statistical Computing) [20], with α set at .001, using the traditional seasonal decomposition by LOESS (locally estimated scatterplot smoothing) method for time series decomposition and the generalized extreme studentized deviate test for anomaly detection. For each detected anomaly, we conducted additional internet searches for potentially relevant current events that could have resulted in atypical media attention or public awareness.

In addition to strict media mentions, MC provides a list of top words in the headlines of a random sample of content matching the query. These top words were used to create word clouds using the wordcloud2 R package after excluding the words "covid," "covid-19," and "coronavirus." [21] Finally, we acquired bias ratings for the top 10 media sources for each treatment query primarily from the AllSides website [22,23]; bias ratings were obtained from the Media Bias/Fact Check website [24] when AllSides [22,23] did not rate a particular media source. Ratings were pulled from mid-pandemic (2021) assessments when possible, or from the closest assessment to that time when not.

State-Level Association Between Treatment-Specific Search Interest and Media Coverage

To visualize geographic heterogeneity in search interest and media coverage, we created heatmaps at the state level

for each treatment using *ggplot2* (Figure S1 in Multimedia Appendix 2) [25]. Using treatment-specific regression models, we assessed the state-level relationship between treatment-specific media coverage and search interest. We considered 3 confounders in the models: political leaning, rurality, and social vulnerability.

Covariates

As COVID-19 treatments were highly politicized during the initial stages of the pandemic [9], we hypothesized that statewide political leaning may have differentially influenced interest in and coverage of specific treatments. We measured statewide political leaning as the percentage of a given state that voted for the Republican Party candidate in the 2020 presidential election, on a 0 to 100 scale [26].

Social vulnerability may also have played a role in treatment interest, given its association with reduced access to health care services [27]. Reduced interaction with health care providers and services has previously been associated with riskier health choices and poor health outcomes, providing evidence that social vulnerability may influence treatment-seeking behavior [27,28]. We measured social vulnerability using the COVID-19 Community Vulnerability Index, which provides a state-level measure of access to health care, taking economic, structural, and demographic barriers into account [29]. State-level scores are scaled continuously from 0 to 100, where 100 represents the highest level of vulnerability.

Lastly, we included rurality in the models, first as a proxy for known barriers to health care that could potentially influence off-label medication use [30], and second because of ivermectin's widespread use on farms as a livestock deworming agent, which we hypothesized could influence search interest, especially among farming communities. Rurality was measured using the 2021 US Census Bureau Urban and Rural dataset [31], which provides the percentage of a given state's population that lives in rural settings, measured on a 0 to 100 scale, with 100 being the most rural.

Additional covariates were considered for inclusion in this analysis and were ultimately rejected. Specifically, we did not feel that broadband access is a confounding factor in the relationship between GT and MC, as broadband access is unlikely to influence whether the media covers COVID-19 treatments (Figure S2 in Multimedia Appendix 2). However, for due diligence, we acquired a broadband access dataset (US FCC Broadband Data Collection, FCC National Broadband Map) [32,33] for May 2024 (the earliest version of the dataset we could locate) and discovered that the median percentage of the United States served by broadband (≥100/20 Mbps) is 94% (IQR 80%-99%), the median percentage for underserved (≥25/3 Mbps but <100/20 Mbps) is 5% (IQR 0.4%-17%), and the median unserved (<25/3 Mbps) is 0% (IQR 0%-0%). These numbers were similar when stratifying by urban/rural status. We therefore chose not to include broadband access in our analysis.

Analysis

Because both search interest and media coverage are bounded indices (0-100) rather than true continuous or count data, we regressed search interest against daily media coverage, and vice versa, for each treatment using a 2-stage process. This allowed us to explicitly model the questions: (1) does a state have any of the outcome (search interest or media coverage), and (2) given a nonzero outcome, how much is it impacted by the exposure? To do this, we used the *glmmTMB* package in R [34] to fit 2 generalized linear mixed models. First, we fit a logistic model to assess the impact of exposure on presence/absence of the outcome. Second, we fit a conditional log-normal model for all nonzero outcomes. This approach was chosen to account for overdispersion in the data because, across most days and states in the dataset outside of the anomalies, there was little search interest or media coverage of the selected COVID-19 treatments.

Media coverage was scaled by dividing values by the root mean square, and the other covariates were mean-centered and scaled by dividing values by the SD to ensure comparability and equal contribution in the regression analysis and to aid interpretation. We included "state" as a random intercept to control for interstate variability in the impact of covariates on exposure. Media coverage and search interest were assessed at 3 relative time points—nonlagged (same day), lagged 1 day, and lagged 2 days—using the *timetk* R package [35]. Multicollinearity was assessed by checking the variance inflation factors for the models. Model results are presented as adjusted odds ratios (ORs, logistic model) and adjusted risk ratios and percent differences (conditional model), with 95% Wald CIs. Multiple comparisons were accounted for using the Bonferroni method, with $P<.001$ considered significant. All analyses were performed using R (version 4.4.x) [36].

To assess whether residual spatial autocorrelation existed beyond what was accounted for by the state-level random effect, we applied the Moran I measure to the state-level mean residuals from all 36 models (18 model pairs across binary and conditional parts), using a queen contiguity spatial weights matrix (Table S1 in Multimedia Appendix 2). E-values, which quantify the minimum strength of association that unmeasured confounders would need to have with both the treatment and the outcome to fully explain away a specific treatment-outcome association, conditional on the measured covariates, were calculated using the *EValue* R package [37].

Ethical Considerations

This study used publicly available aggregated state-level data that do not contain individual-level or identifiable information. Because the data are deidentified and publicly accessible, this study does not constitute human participants research and is therefore exempt from institutional review board approval.

Results

National Trends in Search Interest and Media Coverage

Nationally, the median search interest (out of 100) during the pandemic period (January 2020 through December 2022) was 2.2 (IQR 1.6-3.0) for hydroxychloroquine, 6.0 (IQR 1.9-9.9) for ivermectin, and 2.2 (IQR 1.5-3.3) for remdesivir, compared to 0.5 (IQR 0.3-0.6), 1.0 (IQR 1-1), and 0 (IQR 0-0) for the respective treatments in 2019. Nationally, the median media coverage during the pandemic was 0.05% (IQR 0.02%-0.13%) for hydroxychloroquine, 0.01% (IQR 0%-0.04%) for ivermectin, and 0.03% (IQR 0.01%-0.1%) for remdesivir, compared to median coverage of 0% for each treatment in 2019.

Anomaly detection identified periods of atypical search interest (Figure 1A) and media coverage (Figure 1B). Search interest in hydroxychloroquine peaked in July 2020 with media coverage increasing sharply in March 2020 and remaining high until mid-November 2020. While search interest in ivermectin had several small anomalies prior to 2021, interest peaked in late August/early September 2021, with a second large peak occurring in January 2022. Media coverage of ivermectin peaked and stayed elevated during this same period. Finally, search interest in remdesivir peaked in late April 2020 and decreased quickly; media coverage was high throughout 2020, and coverage remained sporadically elevated through the end of the study period.

Figure 1. National time series of public search interest (Google Trends) and news media coverage (Media Cloud) for the 3 purported COVID-19 treatments—hydroxychloroquine, ivermectin, and remdesivir—in the United States from January 2019 through December 2022. (A) Timeline of contemporaneous COVID-19 treatment–related current events, identified by web searching for relevant news events occurring at the same time as detected anomalies. (B) Daily Google Trends search interest and (C) daily Media Cloud news coverage, with statistically identified anomalies shown in red and nonanomalous time points in gray. The y-axis differs across treatments in panel C, whereas panel B is consistently scaled from 0 to 100, as normalized by Google. FDA: US Food and Drug Administration.

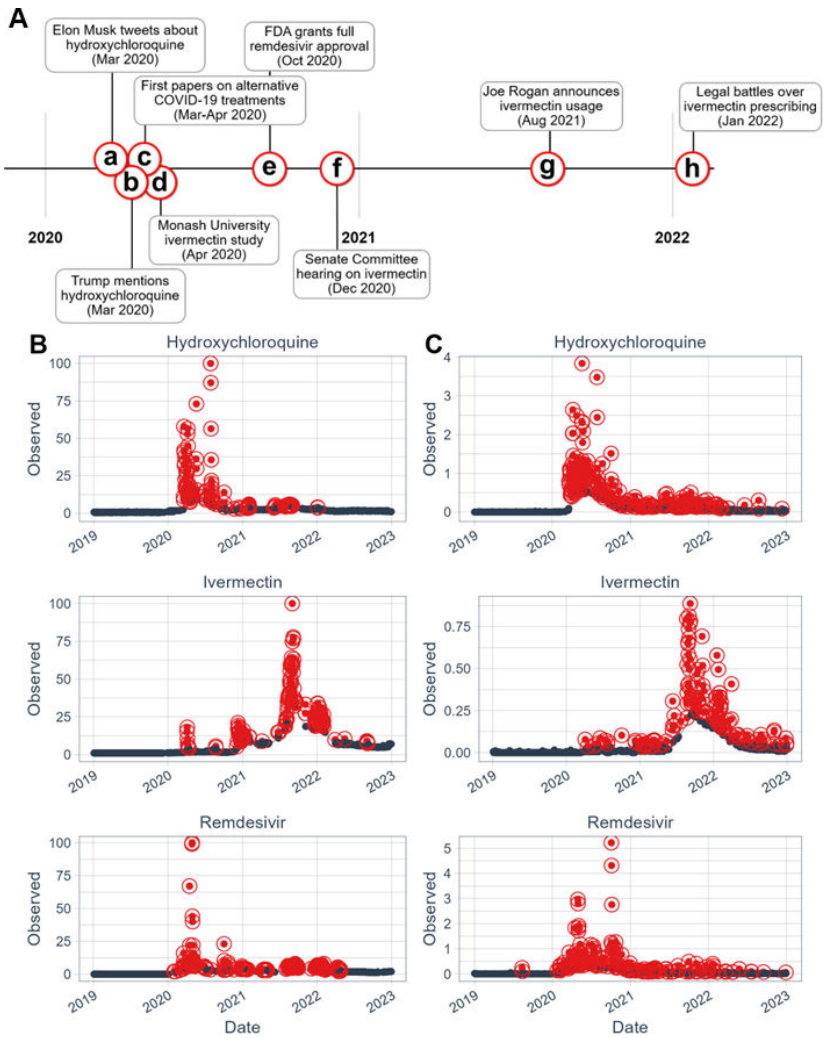


Table 1 shows the top 10 national-level media sources with the highest number of stories matching each treatment query and their bias as determined by 1 of 2 media bias reporting websites during the COVID-19 pandemic. Unsurprisingly, all top sources were web-based. While some sources covered all treatments at a high level (eg, nytimes.com and

washingtonpost.com were in the top 10 for all 3 treatments), there were distinct patterns of bias (Figure 2). The plurality of sources for all treatments were considered "Left" or "Left Leaning"; ivermectin was covered by the highest number of "Right"-biased sources, and remdesivir had the highest coverage by "Center" or "unbiased" sources.

Figure 2. Distribution of political bias categories among the top 10 US news sources covering each of the 3 purported COVID-19 treatments—hydroxychloroquine (HCQ), ivermectin (IVM), and remdesivir (REM)—in a retrospective analysis of Media Cloud news coverage in the United States from January 2019 through December 2022. Each source's bias rating and the year of assessment were obtained from AllSides or, when unavailable, Media Bias/Fact Check [22-24].

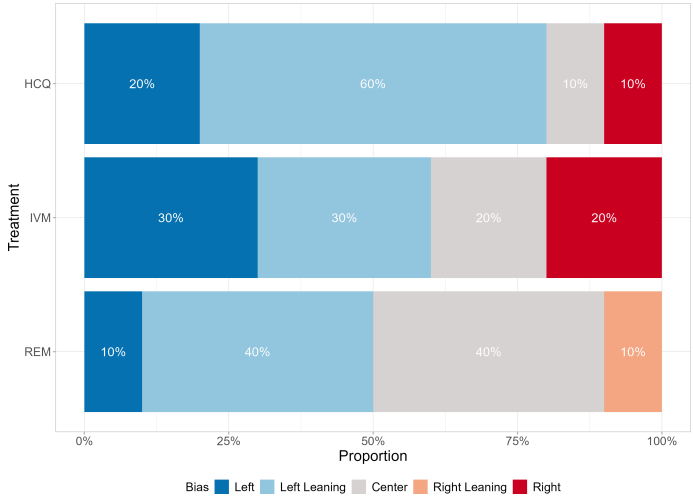


Table 1. Top 10 US national news sources covering each of the 3 purported COVID-19 treatments—hydroxychloroquine, ivermectin, and remdesivir—in a retrospective analysis of Media Cloud news coverage in the United States from January 2019 through December 2022[a].

Rank	Hydroxychloroquine				Ivermectin				Remdesivir			
	Source	Count	Bias	Year	Source	Count	Bias	Year	Source	Count	Bias	Year
1	reuters.com	1498	C[b]	2021	nytimes.com	357	LL[c]	2021	reuters.com	1777	C	2021
2	cnn.com	1402	L[d]	2021	washingtonpost.com	190	LL	2020	nytimes.com	1049	LL	2021
3	nytimes.com	1042	LL	2021	rawstory.com[e]	173	L	2025	cnn.com	889	L	2021
4	washingtonpost.com	935	LL	2020	theguardian.com	170	LL	2021	cbsnews.com	468	LL	2021
5	rawstory.com[e]	628	L	2025	newsweek.com	154	C	2021	cnbc.com	450	C	2022
6	foxnews.com	600	R[f]	2021	foxnews.com	145	R	2021	marketwatch.com	429	C	2020
7	theguardian.com	548	LL	2021	cnn.com	142	L	2021	washingtonpost.com	422	LL	2020
8	usatoday.com	460	LL	2021	dailykos.com[e]	139	L	2024	thestreet.com[e]	397	RL[g]	2020
9	cbsnews.com	379	LL	2021	theblaze.com	129	R	2023	businessinsider.com	362	LL	2022
10	businessinsider.com	365	LL	2022	forbes.com	119	C	2022	benzinga.com[e]	360	C	2021

[a]For each treatment query, sources are ranked by the number of stories mentioning the treatment over the study period. Each source's political bias rating and the year of that assessment were obtained from AllSides or, when unavailable, Media Bias/Fact Check [22-24].
[b]C: Center.
[c]LL: Left Leaning.
[d]L: Left.
[e]Rating from Media Bias/Fact Check.
[f]R: Right.
[g]RL: Right Leaning.

When assessing the co-occurrence of words and phrases in media sources covering each of the treatments (Figures S3A-C in Multimedia Appendix 2), the most striking qualitative difference was in the categories of words appearing alongside the drugs. Specifically, ivermectin appeared to be reported more frequently in association with specific individuals (Figure S3B in Multimedia Appendix 2) than media mentioning hydroxychloroquine (Figure S3A in Multimedia Appendix 2) or remdesivir (Figure S3C in Multimedia Appendix 2), although the top co-occurring word for hydroxychloroquine was "Trump" by a wide margin. In Google searches, people seemed most interested in understanding what hydroxychloroquine is and the uses of ivermectin (eg, "for humans" and "for dogs"). Curiously, for remdesivir, several co-occurring terms included the manufacturer and searches for remdesivir stock rather than its uses (Table 2).

Table 2. Co-occurring Google search terms for each of the 3 purported COVID-19 treatments—hydroxychloroquine, ivermectin, and remdesivir—in a retrospective analysis of Media Cloud news coverage in the United States from January 2019 through December 2022[a].

Search type, search term, and queries	Score
Top searches	
Hydroxychloroquine	
hydroxychloroquine covid	100
is hydroxychloroquine	76
hydroxychloroquine side effects	62
coronavirus hydroxychloroquine	52
does hydroxychloroquine	40
trump hydroxychloroquine	38
hydroxychloroquine for covid	37
what is hydroxychloroquine	33
hydroxychloroquine covid 19	30
hydroxychloroquine sulfate	25
Ivermectin	
ivermectin covid	100
ivermectin for covid	33
ivermectin for humans	24
ivermectin side effects	20
what is ivermectin	19
ivermectin dosage	16
ivermectin dogs	13
ivermectin and covid	12
ivermectin for sale	11
ivermectin uses	11
Remdesivir	
remdesivir covid	100
coronavirus remdesivir	50
remdesivir side effects	42
gilead remdesivir	40
gilead	38
remdesivir for covid	36
remdesivir treatment	31
remdesivir stock	29
what is remdesivir	27
remdesivir drug	27
Rising searches	
Hydroxychloroquine	
coronavirus hydroxychloroquine	Breakout
hydroxychloroquine for covid	Breakout
hydroxychloroquine covid 19	Breakout
hydroxychloroquine and covid	Breakout
ivermectin	Breakout
hydroxychloroquine covid-19	Breakout
hydroxychloroquine for covid 19	Breakout
hydroxychloroquine for coronavirus	Breakout
hydroxychloroquine covid	Breakout
fauci	Breakout
Ivermectin	
ivermectin covid	Breakout

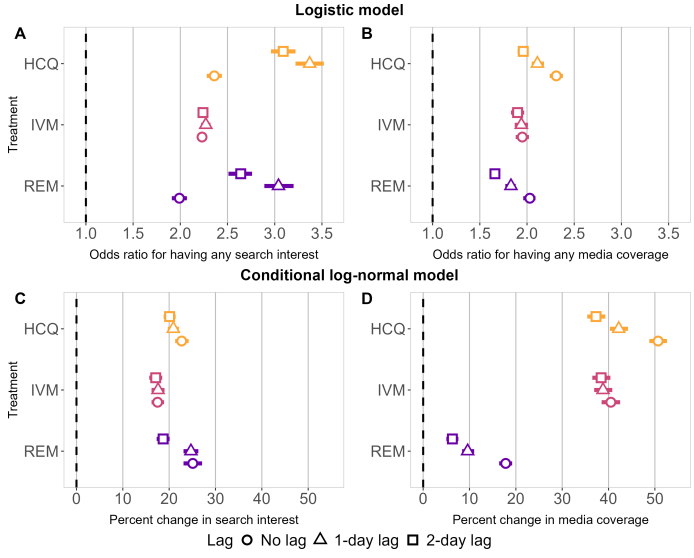
Search type, search term, and queries	Score
ivermectin for covid	Breakout
ivermectin and covid	Breakout
ivermectin in covid	Breakout
ivermectin covid 19	Breakout
covid treatment	Breakout
joe rogan	Breakout
ivermectin joe rogan	Breakout
ivermectin covid-19	Breakout
ivermectin dosage covid	Breakout
Remdesivir	
remdesivir covid	Breakout
coronavirus remdesivir	Breakout
remdesivir side effects	Breakout
remdesivir for covid	Breakout
what is remdesivir	Breakout
remdesivir drug	Breakout
covid 19	Breakout
remdesivir covid treatment	Breakout
remdesivir cost	Breakout
trump remdesivir	Breakout

[a]Per Google, "Top searches" are terms most frequently searched together with the queried term in the same session within the chosen category and region; "Rising searches" are terms with the greatest growth in volume over the period, shown as a percentage increase relative to the prior period, with "Breakout" indicating growth exceeding 5000%.

State-Level Trends in Search Interest and Media Coverage

When controlling for average state political leaning, rurality, and social vulnerability, we found significant, positive associations between media coverage and search interest across all 3 treatments for the questions: (1) does a state have any of the outcome (Figure 3A and B), and (2) given a nonzero outcome, how much is it impacted by the exposure (Figure 3C and D)?

Figure 3. State-level associations between news media coverage (Media Cloud) and public search interest (Google Trends) for the 3 purported COVID-19 treatments—hydroxychloroquine (HCQ), ivermectin (IVM), and remdesivir (REM)—from a retrospective 2-step regression analysis across US states from January 2019 through December 2022, adjusted for state political leaning, rurality, and social vulnerability and assessed at same-day, 1-day, and 2-day lags. Logistic models show (A) the odds ratio of any search interest given any vs no media coverage and (B) the odds ratio of any media coverage given any vs no search interest. Conditional log-normal models show, among nonzero observations, (C) the percent change in search interest as media coverage increases, and (D) the percent change in media coverage as search interest increases. Shapes indicate days of lag between exposure and outcome. Bars are 95% confidence intervals.



For public search interest, the odds of having any interest peaked at a 1-day lag for both hydroxychloroquine (OR 3.48, 95% CI 3.32-3.64) and remdesivir (OR 3.06, 95% CI 2.91-3.23), relative to their immediate, no-lag baselines (OR_H 2.37, 95% CI 2.29-2.46 and OR_R 1.96, 95% CI 1.89-2.05; Figure 3A). Conversely, ivermectin maintained remarkably stable threshold OR across all time frames, ranging tightly from an OR of 2.36 (95% CI 2.31-2.42) at no lag to 2.39 (95% CI 2.33-2.45) at a 1-day lag. In contrast to this delayed or sustained public search behavior, the relationship with media coverage showed immediate temporal decay across all treatments. The highest odds of a treatment having any media coverage occurred with no lag for hydroxychloroquine (OR 2.29, 95% CI 2.22-2.36), ivermectin (OR 1.92, 95% CI 1.85-2.00), and remdesivir (OR 1.98, 95% CI 1.92-2.05); all associations steadily weakened as the lag extended to 2 days.

Conditional log-normal models evaluating the volume of search interest or media coverage among nonzero observations revealed similar patterns to the logistic models (Figure 3C and D). For example, hydroxychloroquine again demonstrated the most pronounced effects of the 3 treatments; media coverage increased same-day search interest by 21.3% (95% CI 20.1%-22.5%), and search interest increased same-day media coverage by 30.4% (95% CI 26.3%-31.6%). Unlike the logistic models, the timing of the exposure relative to the outcome had a much more limited effect. While hydroxychloroquine search intensity steadily waned over the lag periods, falling to 17.7% (95% CI 16.6%-18.8%) at a 2-day lag, remdesivir search interest peaked at a 1-day lag (15.7%, 95% CI 14.8%-16.6%) before declining by day 2 (14.7%, 95% CI 13.8%-15.6%). Ivermectin displayed notable consistency throughout, with conditional search interest remaining stable between 17.2% and 18.2% (95% CI range: 15.7%-19.7%), and conditional media coverage steady around 16% across all timeframes (Figure 3C and D). Notably, despite remdesivir demonstrating a strong association with the initial onset of public search interest, its relationship with subsequent media coverage was the weakest observed, yielding an 8.4% (95% CI 7.6%-9.3%) increase at no lag that decreased to only 4.6% (95% CI 3.6%-5.6%) when lagged 2 days (Figure 3D). All regression values and fitness statistics can be found in Tables S2 and S3 in Multimedia Appendix 2.

To evaluate the vulnerability of these findings to unmeasured confounding, we calculated E-values for both the logistic and conditional models. For the logistic models, the associations proved highly robust; an unmeasured confounder would need to be associated with both treatment exposure and the outcome by a risk ratio ranging from 1.82 to 3.05 (based on the lower confidence limits) to fully explain away the observed probabilities of generating any search interest or media coverage. For the conditional models, the E-values were transformed into percentage changes to align with the effect size scale. These results indicate moderate to high robustness depending on the treatment. To shift the observed percentage changes in volume to the null, an unmeasured confounder would need to independently produce an effect ranging from a 22.9% change (for remdesivir media coverage at a 2-day lag) up to a 90.8% change (for hydroxychloroquine media coverage at no lag). While the findings for hydroxychloroquine remain highly robust against unmeasured confounding, the more modest E-values for remdesivir's delayed media coverage suggest those estimates are more sensitive to moderate unmeasured confounding (Table S2 in Multimedia Appendix 2).

Discussion

Principal Findings

In this study, we identified significant public interest in 3 purported COVID-19 treatments—hydroxychloroquine, ivermectin, and remdesivir—as represented by anomalies detected in heightened search interest in these medications during the pandemic period. Additionally, we found significant associations between news media coverage and all 3 treatments. Our bidirectional design allows us to evaluate the reflection hypothesis—the proposition that media coverage functions as a mirror of existing public interest rather than its driver—directly against the data. If public interest were the primary driver of media coverage, we would expect search interest to predict subsequent media coverage at least as strongly as coverage predicted search interest. Instead, we observed a consistent asymmetry: across all 3 treatments and all lag structures, the association between media coverage and subsequent search interest was substantially stronger than the reverse, with the association between search interest and media coverage for remdesivir decreasing to a 4.6% (95% CI 3.6%-5.6%) increase at a 2-day lag. This pattern suggests that, for these purported COVID-19 treatments during this period, the influencing role of news media outweighed its reflective role. The reflection hypothesis is unlikely to be entirely inoperative; coverage and interest are mutually reinforcing, and our aggregate, state-level design cannot adjudicate causal direction at the individual level or rule out unmeasured events driving both series simultaneously. Rather, we have found that, in a fast-moving emergency dominated by many scientific and clinical unknowns, public interest appears to have followed media attention more than preceded it. This distinction matters for public health practice, as it implies that proactive, accurate news coverage can shape the information landscape rather than merely echo public sentiment that has already formed.

At the beginning of the pandemic, substantial uncertainty surrounded the epidemiology of COVID-19 and the effectiveness, safety, and availability of potential treatments. As scientific evidence accumulated, public health guidance evolved accordingly to reflect updated knowledge [38]. Although changing recommendations are expected during the early stages of a novel pathogen outbreak, inconsistent or insufficiently transparent messaging may have contributed to public confusion. In this environment, many individuals increasingly relied on nonexpert sources such as politicians, public figures, and celebrities for health-related information rather than traditional public health authorities [5]. Scholars have long noted that media reporting practices can further shape public risk perception; anecdotal framing and selective emphasis may lead audiences to draw inaccurate conclusions

about the magnitude or nature of risk [39]. Additionally, because many journalists lack formal training in statistics or probability, complex or preliminary scientific findings may not always be critically evaluated before dissemination to mass audiences, potentially amplifying misunderstanding or misinterpretation [40].

These dynamics may have been compounded by declining access to medical guidance: recent studies report that the percentage of Americans who regularly see a primary care physician has steadily decreased from 2014 to 2022, meaning regular communication with licensed medical providers is becoming more limited for many communities across the United States [41]. Together, these factors may have contributed to the general public's increasing reliance on news media for guidance during the COVID-19 pandemic. Indeed, over the last several years, perceived US media influence on government decisions has grown among the public and will likely continue to have an outsized influence on the public interest [42]. In communication research, this aligns with media system dependency theory, which assumes that the impact of information provided by news media on audience perceptions is a function of how dependent an audience member is on mass media as a source for acquiring information important to them [43]; that is, the more likely someone is to turn to news media for personally relevant information, the more *dependent* on it they become. Importantly, research has found that this dependency is what drives changes in behavior, not media usage alone. While our study did not directly assess media usage or dependency at the individual level, the patterns observed, particularly the strong, temporally immediate association between media coverage and search interest, are consistent with media system dependency theory and highlight the importance of integrating communication theory into future epidemiologic analyses of health information seeking.

We found that the effect of media coverage on same-day search interest was largest for hydroxychloroquine, an initially FDA-authorized treatment with early potential that ultimately proved ineffective and dangerous [1], followed by ivermectin, an incredibly popular but inappropriate treatment for COVID-19, and remdesivir, the only treatment that remains FDA-approved for use [3,4]. Although ivermectin produced an intermediate same-day effect, it was the only drug for which search interest stayed significantly elevated at a comparable level 1 to 2 days after coverage by media outlets, whereas the effects for hydroxychloroquine and remdesivir were more transient. One possible explanation for this sustained response is that people may receive information about ivermectin more frequently through non-news media sources, such as personal networks, social media, or podcasts, which may see continued high levels of engagement days to weeks after posting, depending on the platform [44]. Another hypothesis for why search interest in ivermectin remained elevated rather than tracking closely with day-to-day media coverage relates to trust in traditional media. Research by Ladd [45] suggests that individuals who distrust traditional news media sources are more likely to rely on preexisting political beliefs to form opinions rather than incorporating new information supplied by news media. At least one study [46] has found that higher belief in COVID-19 vaccine misinformation and conspiracy thinking was associated with increased use of ivermectin and/or hydroxychloroquine, although the results were not stratified by specific treatment. In a more recent article, Ladd and Podkul [47] argue that when media credibility is lost, so is its capacity to influence the public. In this context, diminished trust in traditional media and reliance on alternative information channels may attenuate or delay the observable impact of news coverage on public search behavior.

We note several limitations in this analysis. First, the state-level analysis includes only state-level media outlets, as MC cannot track state-level readership of national news sources. Given that many individuals rely heavily on national media outlets for news, the media exposure used in this analysis may be skewed if individuals within a state engage differently with national-level vs state-level news outlets. Additionally, larger states had relatively larger news media corpora than smaller states; however, no corpus included fewer than 30 sources, indicating that sample sizes were sufficient to assess news media coverage at this geographic scale. While the associations reported here were broadly robust to unmeasured confounding, the E-values for remdesivir's delayed media coverage were comparatively modest, indicating that those particular estimates are more sensitive to moderate unmeasured confounding and should be interpreted with corresponding caution. Notably, MC does not capture sentiment (ie, the emotions and attitudes contextualizing a news report about a particular issue), meaning that we were unable to comment on whether the treatment-related news media sources were reporting positively or negatively on purported treatments. Future studies should assess the content and sentiment of health-related news articles to understand the kind of language that is most likely to prompt heightened search interest, so those techniques can be leveraged to improve health communication strategies. Relatedly, our analysis captured only 2 information channels, news media (via MC) and search behavior (via GT), and did not measure exposure to other sources that may have influenced health information seeking during the study period, including social media platforms, podcasts, messaging applications, and personal networks. This is particularly relevant for ivermectin, for which we hypothesized that non-news channels may have contributed to the sustained search interest we observed; without data from these sources, we cannot directly test that hypothesis or quantify the relative contribution of alternative information channels to public interest in any of the 3 treatments.

Limitations in the use of GT data also exist. GT normalizes search interest independently for each geographic region (ie, state). Consequently, a search value of 100 in one state does not represent the same search volume as a search value of 100 in another state. For example, if Maryland has 500 total searches and 50 are for "ivermectin," the scaled search interest value would be 100. If California has 5,000,000 total searches and 100 are for "ivermectin," which might also yield a value of 100, even though the underlying population-level

search behavior is completely different. Thus, these results are not intended to be compared between states; our analysis is intended to assess temporal patterns in our outcomes of interest, while accounting for state-level variation in search behavior and media coverage. Lastly, search interest was only captured for the population using Google as their primary search engine; people using alternative engines such as Microsoft Bing or DuckDuckGo were not captured in our study, and these users might differ in characteristics such as political leaning that could make their search behavior fundamentally different from that of Google users. However, in the United States, the Google search engine accounts for nearly 90% of market share [48]; we are, therefore, confident that our results capture most relevant search interest.

Several features of the media environment have continued to evolve since the end of our study period in 2022, with implications for how these findings should be applied to future public health emergencies. The audience for traditional and web-based news outlets (the corpus captured by MC) has continued to fragment, with a growing share of the public encountering health information through algorithmically curated social feeds, messaging applications, video platforms, and individual content creators rather than through identifiable news organizations [49,50]. The continued contraction of local news coverage may further widen the gap between national and subnational information environments that our state-level analysis was only partially able to capture [51].

More recently, the integration of generative AI into search and the growth of conversational information-seeking may alter both what "search interest" reflects and how the public is exposed to health claims [52,53], potentially decoupling search behavior from discrete news events in ways our lag-based framework was not designed to detect. For example, in 2024, only 1% of COVID-19-related search queries were answered by AI; this increased to more than 66% by 2025 [53]. However, these shifts do not undermine our central finding that news media coverage was strongly and contemporaneously associated with public search interest during the COVID-19 pandemic; rather, they suggest that the relative influence of traditional news media may be diminishing, and that the sustained, media-independent interest we observed for ivermectin may become a more common pattern as alternative information channels assume a larger role. Consequently, while news media remains an important lever for public health communication, future efforts will likely need to engage a broader and more decentralized set of information channels to reach at-risk populations effectively.

Conclusions

Regardless of the quality of public health messaging available to the general public, social media, news outlets, and political and public figures will continue to be major influences on how individuals seek health-related guidance. During a public health emergency, the information that populations access can directly influence health-seeking behaviors, with potentially life-threatening consequences. More broadly, positive media coverage of unsafe or unapproved medications can deter individuals from trusting and accessing safe alternatives that are more likely to be efficacious in preventing disease progression. Given the observed associations between treatment-related news media coverage and public interest in said treatments, our results suggest that news media serve as a powerful mechanism for experts to inform the landscape of public opinion and to reach audiences during future public health emergencies.

Generative AI Use

ChatGPT (GPT-5.3; OpenAI) was used to assist with minor language editing and to improve the clarity of select manuscript text. Claude (Sonnet 4.6; Anthropic) was used for minor R code development and formatting during the manuscript review stage. All content was critically reviewed, verified, and approved by the authors, who take full responsibility for the final manuscript.

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Data Availability

All data used in this study are available through public databases. Project-specific GT and MC data, along with annotated study code, can be found on GitHub [54].

Authors' Contributions

MSM and EER conceptualized the study. BL, EER, and TB were responsible for data acquisition. BL and EER conducted the data analysis and created all figures. All authors contributed to data interpretation. BL and EER wrote the initial draft of the paper. EER, BAS, FABC, and CRB wrote the second draft. All authors contributed to editing the manuscript and approved the final version.

Conflicts of Interest

MSM has previously received fellowship funds from Moderna, Inc.

Multimedia Appendix 1

Google Trends data extraction.
[DOCX File (Microsoft Word File), 19 KB-Multimedia Appendix 1]

Multimedia Appendix 2

Supplemental results. Supplemental results for the state-level analysis of news media coverage (Media Cloud) and public search interest (Google Trends) for three purported COVID-19 treatments (hydroxychloroquine, ivermectin, and remdesivir) across US states, January 2019–December 2022. Table S1 reports residual spatial autocorrelation diagnostics (Moran's I) for the same-day, 1-day, and 2-day lagged two-step (logistic and conditional log-normal) models. Table S2 gives the full regression output, adjusted for political leaning, rurality, and social vulnerability, with E-values for robustness to unmeasured confounding. Table S3 gives model fit statistics (AIC, BIC, log-likelihood, ICC, and conditional and marginal R^2). Figure S1 shows state-level time series of search interest and media coverage. Figure S2 is a directed acyclic graph of the hypothesized causal relationships and candidate confounders. Figure S3 shows co-occurring headline words for each treatment.
[DOCX File (Microsoft Word File), 1325 KB-Multimedia Appendix 2]

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Abbreviations

FDA: US Food and Drug Administration
GT: Google Trends
LOESS: locally estimated scatterplot smoothing
MC: Media Cloud
OR: odds ratio

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