Do Your Own Research: How Searching Online to Evaluate Misinformation Can Increase Its Perceived Veracity

Kevin Aslett[a], Zeve Sanderson[b], William Godel[b], Nathaniel Persily[d], Jonathan Nagler[b,c], and Joshua A. Tucker[b,c]

[a]School of Politics, Security and International Affairs, University of Central Florida
[b]Center for Social Media and Politics, New York University
[c]Wilf Family Department of Politics, New York University
[d]Stanford University Law School, Stanford University

Abstract

With misinformation introducing challenges in domains ranging from public health to democratic governance, significant attention has been paid to understanding the spread of and belief in online misinformation, with a particular focus on social media platforms. However, the dominant role of search engines in the digital information ecosystem remains under-explored, even though the use of online search to evaluate the veracity of false or misleading news is a central component of media literacy interventions encouraged by technology companies, government agencies, and civil society organizations alike. While conventional wisdom suggests that searching online when evaluating the veracity of misinformation would reduce belief in it, there is little empirical evidence with which to evaluate this claim. Across five experiments, we present consistent evidence that online search to evaluate the truthfulness of false news articles actually *increases* the probability of believing misinformation. To shed light on this relationship, we combine survey and digital trace data, collected using a custom browser extension. We find that the search effect is concentrated among individuals for whom search engines return lower-quality information. Our results demonstrate that those who search online to evaluate misinformation risk falling into data voids, or informational spaces where there is corroborating evidence from low-quality sources. We also find consistent evidence that searching online to evaluate news (SOTEN) increases belief in true news from low quality sources, but no consistent evidence that it increases belief in true news from mainstream sources. Our findings highlight the need for media literacy programs to ground their recommendations in empirically tested interventions and search engines to invest in solutions to the challenges identified here. Building off of this, media literacy programs should supplement a general recommendation to search online with more targeted techniques that teach individuals how to use proper search terms.

Introduction

Concern over the impact of misinformation has continued to grow, as high levels of belief in misinformation have threatened democratic legitimacy in the United States[1] and global public health during the COVID-19 pandemic.[2] Significant attention among scholars, media, and policymakers alike has been paid to the role of social media platforms in the spread of, and belief in, misinformation (Allcott et al., 2019; Persily and Tucker, 2020), with comparatively little focus on other central features of the digital information ecosystem.

This gap in research is particularly evident in our limited understanding of the effect of search engines. While recent research has explored the potential partisan biases of search engine results (Hu et al., 2019; Kaňuková et al., 2019; Robertson et al., 2018), relatively little is known about a fundamental but understudied question: how does searching online to evaluate news (SOTEN) impact belief in misinformation? As the cost of producing and distributing information online has fallen and the sheer volume of information on the internet has risen, reliance on traditional gatekeepers has been significantly reduced, leaving search engines to fill the role of 21st century gatekeepers by sorting and validating online content for the public (Jürgens and Stark, 2017; Latzer et al., 2016). In this new role, search engines have become influential in users' political knowledge (Granka, 2010) and public opinion (Latzer et al., 2016). A majority of internet users state that they check facts online they come across at least once a day, and many believe that results from search engines are more reliable than traditional news, such as radio, newspapers, or television (Dutton et al., 2017). The growing reliance on search engines for information verification has been encouraged by social media companies,[3] civil society,[4] and government agencies,[5] all of which have invested in campaigns to encourage online users to research news they believe may be suspect through online search engines with the goal of reducing belief in misinformation. Although search engines play a key role in how people evaluate information online, we know little about how SOTEN impacts

[1] Misinformation about the 2020 Presidential Election in the United States helped fuel the riots at the U.S. Capitol on January 6th, 2021 (Boggioni, 2021; Edwards, 2021; Greenspan, 2021; McCarthy, n.d.)

[2] Misinformation about the COVID-19 vaccine has lowered intent to get vaccinated (Loomba et al., 2021).

[3] In 2017, Facebook listed a link to ten tips for spotting fake news and one tip asked the readers to "look at other reports. If no other reputable news source is reporting the same story, it may indicate that the story is false." (Constine, 2017)

[4] See https://www.wnyc.org/story/breaking-news-consumer-handbook-fake-news-edition/.

[5] In 2021, the United States Surgeon General released "A Community Toolkit for Addressing Health Misinformation" that recommended searching for additional information from credible sources" https://www.hhs.gov/sites/default/files/health-misinformation-toolkit-english.pdf

belief in misinformation.

Research on interventions designed to mitigate belief in misinformation has developed in recent years, but work has thus far focused on ideological congruence (Allcott and Gentzkow, 2017; Moravec et al., 2018), psychological factors (Pennycook and Rand, 2019, 2020), and digital media literacy (Guess et al., 2020). In this manuscript, we present for the first time, to our knowledge, the results from experimental studies identifying how SOTEN affects belief in misinformation. Specifically, we test a pre-registered hypothesis that searching online to verify the veracity of false or misleading articles *increases* belief in them, contradicting what we believe to be the received wisdom underlying many digital media literacy interventions.[6] We then explore a possible mechanism for why belief in false/misleading articles is increased by searching online to evaluate these articles: exposure to unreliable information. Although it is plausible that searching online may lead respondents to reputable sources contradicting the false article's central claim, theoretical work on information systems has suggested that there are topics or terms for which there exists a high concentration of unreliable information available to be returned by search engines (Golebiewski and boyd, 2019), particularly in the period directly after publication of false content. Online searches in these cases may expose users to other low-quality information, but thus far no empirical evidence has evaluated the extent to which low-quality information is returned by search engines and whether or not exposure to it affects belief in misinformation. Given that the average online media diet is comprised of substantially more true than false news (Allen et al., 2020; Grinberg et al., 2019; Guess et al., 2018), we also seek to understand how SOTEN impacts belief in true news, enabling us to more comprehensively evaluate the potentially heterogeneous effects of online search. Since a number of digital literacy guides focus specifically on identifying misinformation, our main analyses are limited to the effect of search on belief in misinformation; however, to better understand the impact of searching, we also present results from tests of our pre-registered hypothesis that searching online to verify the veracity of true articles increases belief in those articles.

To this end, we run five separate experiments that measure the effect of SOTEN on belief in false and true news stories. Four of these studies utilize survey experiments, while the fifth combines survey and digital trace data. In our first four studies, we measure the effect of SOTEN on belief in highly popular false and true news stories by utilizing different experimental designs (within-

[6] https://osf.io/akemx/

subjects and between subjects) and in a variety of contexts. Study 1 tests the effect of SOTEN on belief in both highly popular false/misleading and true news directly after an article's publication (within 48 hours) using a randomized controlled trial where participants were randomly assigned to one of two groups: the treatment group, in which respondents were encouraged to search online to help them evaluate randomly assigned news articles; or the control group, in which they were not encouraged to search online. Given that consumers of false news online often encounter these stories shortly after publication,[7] we collected respondent evaluations and digital trace data within 48 hours of publication. A study run months or years after publication would test the impact of a different information environment, and it would be impossible to replicate the original search results from the period of most likely exposure. In addition, it is important that we test the effect of SOTEN in real time because misinformation often arises in an uncertain and dynamic information environment where individuals feel a psychological need for understanding (DiFonzo and Bordia, 2007). To measure the effect of SOTEN on belief in misinformation, we run this study during the period—and thus within the information environment—that misinformation was originally generated and most likely to be consumed.[8] In Study 2, we test whether the effect of SOTEN can change an individual's evaluation after they had already assessed the veracity of a news story. The third study (Study 3) is another within-subjects design that measures the effect of SOTEN months after publication, rather than directly after publication, while Study 4 (also a within-subjects design) measures the effect of SOTEN on recent news about a salient topic with significant news coverage (in our case, the Covid-19 pandemic). In each study, individuals in the treatment group receive a set of recommendations, provided to us by a partner organization, encouraging the use of online search to evaluate the news articles presented in their survey instrument.[9] In the fifth and final study, we run a between-respondent study that combines survey and web-tracking data to identify the effect of exposure to low and high quality search engine results on belief in popular misinformation within 72 hours after publication. By collecting search results using a custom web

[7]Online misinformation on social media spreads rapidly (Vosoughi et al., 2018), but also dies out relatively quickly (Starbird et al., 2018)

[8]Given this, we are testing this search effect in the time period in which our studies run (from Study 1 in late 2019 to Study 5 in late 2021). It is possible that, over time, the online information environment may change as the result of new search strategies and/or search algorithms.

[9]The instructions can be found in the Methods and Materials section. In a sixth study, we also tested whether the effect dissipated when we modified these instructions, and we found the effect remained largely similar. The explanation of and results from this study can be found in Section R of the Supplementary Materials.

browser plug-in, we can identify how the quality of these search results may affect users' belief in the misinformation being evaluated.

For all five of the studies, we utilized a pipeline (also pre-registered) that sourced the most popular articles from a variety of "streams" of potential articles, and then distributed the articles to respondents and professional fact-checkers.[10] To remove the possibility of researcher selection bias when selecting the news stories to be sent to respondents for assessment, we developed a transparent and replicable article selection algorithm. More specifically, we sourced the most popular article published in the previous 24 hours from five news streams: liberal mainstream news domains; conservative mainstream news domains; liberal low-quality news domains; conservative low-quality news domains; and low-quality news domains with no clear political orientation. We then sent the popular articles — the veracity of which was established by the panel of professional fact-checkers — to be evaluated by respondents within 24-48 hours of their publication. (See the Methods section for a full explanation of this process.).

Taken together, the five studies provide consistent evidence that SOTEN increases belief in misinformation. In our fifth study, added to test explanations for the mechanism underlying this effect, we find evidence suggesting that exposure to lower-quality information in search results is associated with a higher probability of believing misinformation, but exposure to high-quality information is not. In addition, to fully evaluate the effect of recommending individuals to search online, we also measure the effect of searching online to evaluate true news. In the aggregate, we find that there is a search effect on belief in true news that is similar to the search effect on belief in false/misleading news: searching makes study participants more likely to believe that true news stories are true. However, when we subset the results by the quality of source, we find that while online search increases belief that true news from low-quality sources is true, there is no effect on believing true news from mainstream sources is true. Our results provide important and novel evidence of the effect of SOTEN on news discernment. In particular, our study highlights that online search increases belief in false articles, a potentially harmful effect driven by low-quality search results.

[10]The streams utilized in the studies included low quality news sources that were left leaning, right leaning, and with no clear ideological leaning, as well as mainstream news sources that were left learning and right leaning. All but two of the news stories identified as false/misleading by our professional fact checkers – which form the basis for our analyses in this paper – came from low quality news sources. See the Methods section for more details.

Effect of Searching Online to Evaluate Misinformation on Belief In Misinformation

Our first study (Study 1) tests the effect of SOTEN on belief in misinformation using a randomized controlled trial. We recruited 3,006 respondents living in the United States through Qualtrics, an online survey firm, over ten days and presented them with three articles from mainstream and low-quality sources within 48 hours of publication.[11] Participants were either randomly assigned to be encouraged to search online to help them evaluate all of the articles they were sent (Treatment Group) or were not prompted to search online (Control Group). All respondents were then asked to evaluate the veracity of the article using both a categorical (True, False/Misleading, Could Not Determine) and 7-point ordinal scale. A key challenge was establishing the veracity of the articles directly after publication, a period during which assessments from fact-checking organization were not likely to be available. To this end, we sent out the articles to be evaluated concurrently by a group of six professional fact-checkers from leading national outlets. Fact-checkers could label articles as either "true", "false or misleading", or "could not determine."[12] We labeled articles as "false or misleading" if the modal fact checker evaluation was that the article was false or misleading. Likewise, we labeled articles as "true" if the modal fact checker evaluation was that the article was true.[13] In this section, we only analyze the effect of searching online on belief in articles labeled as "false/misleading." During Study 1, across thirteen false/misleading news articles, we collected 1,145 evaluations from 876 unique respondents in the control group and 1,130 evaluations from 872 unique respondents in the treatment group.[14]

To estimate the treatment effect of being encouraged to search online, we fit an OLS regression model with article-level fixed effects and standard errors clustered at the respondent and article

[11] More details about the respondent recruitment, the article selection selection, and how we determined the veracity of each article can be found in the Methods section.

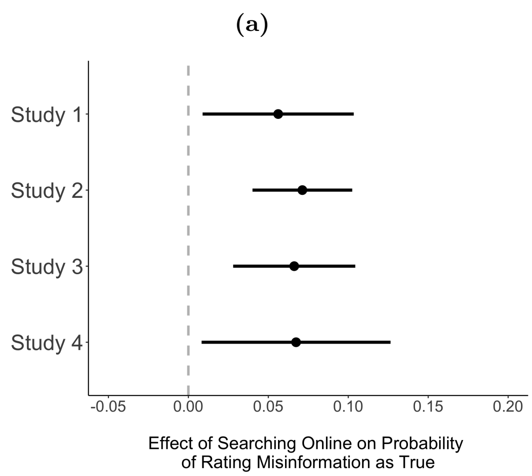
[12] In Studies 4 and 5, the professional fact-checkers rated the articles 24 hours before the respondents so that we could show respondents the fact-checker's rating of each article immediately after completion of the survey.

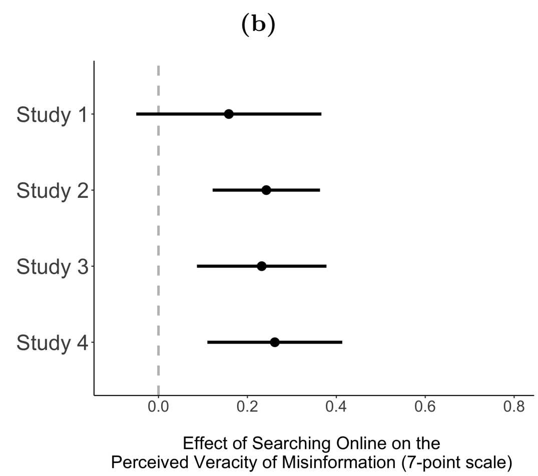
[13] We labeled articles as "could not determine if there was no unique mode or the modal fact-checker evaluation was "could not determine."

[14] Details about these articles can be found in Section A1 of the Supplementary Materials.

level[15] to predict belief in misinformation (i.e. rating a false or misleading article as true).[16] We control for basic demographic factors (age, education, income, ideological congruence, and gender) and, unless noted otherwise, all models in this manuscript follow these specifications. In Row 1 of Figures 1a and 1b we present the treatment effect from Study 1 on belief in misinformation using both a dichotomous outcome (rating a false/misleading story as true: 1=Yes ; 0=No) and a 7-point ordinal scale of veracity belief, respectively.[17] Figure 1a shows that being encouraged to search online increased the probability a respondent rated a false or misleading article as true by 0.057 (P=0.037, Cohen's D = 0.12; for the full regression table, see Section B of the Supplementary Materials). Figure 1b shows a 0.16 increase in perceived veracity using a 7-point ordinal scale (P=0.154, Cohen's D = 0.09).

Figure 1: The effect of searching online to evaluate misinformation on belief in misinformation across Studies 1 through 4. Panels a and b present effect sizes and 95 percent confidence intervals for linear regression models testing the effect of SOTEN during Studies 1, 2, 3, and 4. Panel a presents the effect of SOTEN on rating misinformation as true. Panel b presents the effect of SOTEN on a 7-point ordinal scale of veracity.





We then set out to test whether the search effect was strong enough to change an individual's evaluation after they had already assessed the veracity of a news story. To do so, we ran a within-

[15] We also estimate the treatment effect using our preregistered specification: linear regression model with standard errors clustered on the participant. Results for this model can be found in Section O of the Supplementary Materials. The results in our preregistered model are actually stronger than those reported in the paper. An explanation for why we deviated from this specification can be found in the Methods section.

[16] For our dichotomous outcome, rating a false/misleading story as true (1=Yes ; 0=No), OLS or logistic regressions produce similar results and are both appropriate. An OLS regression is preferred to estimate the causal effects of treatments on a binary outcome (Gomila, 2020).

[17] For the full regression tables see Section B of the Supplementary Materials.

respondents study (Study 2) that asked respondents to evaluate an article without being encouraged to search online and then evaluate the same article again, but after being encouraged to search online. If we assume that respondents have a bias towards consistency, this offers an even stronger test than in Study 1 because, to find a search effect, respondents would have to change their previous evaluation. To conduct the study, we recruited 1,054 American respondents through Qualtrics over 33 days who were presented with one false/misleading popular online article within 48 hours of publication.[18] We then compared their evaluation before being encouraged to search online (control) and their evaluation after being encouraged to do so (treatment). Row 2 of Figures 1a and 1b present the treatment effect from this study using the categorical and ordinal scale. Intriguingly, we find slightly stronger results relative to the first study: searching online increases the probability that a respondent rates a false/misleading article as true by 0.071 (P<0.0001, Cohen's D = 0.15) and an increase in 0.22 (P=0.0004, Cohen's D = 0.13) on a 7-point ordinal scale.[19] We also find that among those who first rated the false/misleading article correctly as false/misleading, 17.6% changed their evaluation to true after being prompted to search online. For comparison, among those who first incorrectly rated the article as true, only 5.8% changed their evaluation to false or misleading after being required to search online. Among those who could not determine the veracity of the article initially, more individuals incorrectly changed their evaluation to true than to false/misleading after being required to search online. This suggests that searching online may falsely raise the confidence of individuals evaluating false/misleading news.

These first two studies present consistent evidence that searching online increases belief in misinformation directly after its publication. However, misinformation can in some instances go viral weeks or months after publication. In these instances, the online information environment surrounding the false article could be different from the one encountered in the first 72 hours. Directly after publication of false articles, search engines may return similar misinformation and little credible information because professional fact-checks often take days or weeks to be published (Kalsnes, 2018). Therefore, we might expect that as time passes post-publication, individuals searching online would be exposed to more professional fact-checks and credible information when SOTEN. This high quality information could eliminate, or, even more optimistically, change the

[18] Details about these articles can be found in Section A2 of the Supplementary Materials.

[19] For the full regression table see Section B of the Supplementary Materials.

direction of the search effect identified in Studies 1 and 2. Of course, as most searches to check the veracity of misinformation would likely occur immediately or soon after publication, we think the findings from Studies 1 and 2 more closely capture the likely impact of online search.

To measure the effect of SOTEN on belief in misinformation months after publication, we ran a third study (Study 3) that replicates Study 2 with new respondents evaluating the same set of articles. A key difference is that the study is run between three and six months after publication of the articles. To conduct this study, we recruited 2,022 American respondents over one month through Qualtrics who evaluated false/misleading articles first without being encouraged to search online and then again after being encouraged to search online. Row 3 of Figures 1a and 1b present the effect of SOTEN in Study 3 using the categorical and ordinal scale. We find slightly weaker but similar results relative to Study 2: searching online increases the probability that a respondent rates a false/misleading article as true by 0.066 (P=0.0018, Cohen's D = 0.14), which means 18% more respondents rated the same false/misleading story as true after they were asked to re-evaluate the article post-treatment.[20] A similar effect was identified using an ordinal scale (0.22 increase on a 7-point scale ; P=0.0038, Cohen's D = 0.13). So while it may be possible that respondents were exposed to more reliable information months after publication, it does not appear to have negated the impact of SOTEN on belief in misinformation.

The first three studies measure the effect of SOTEN on popular pieces of misinformation, which may cover niche topics not reported on by reliable news outlets. However, it is possible that when one searches online when evaluating misinformation about salient events, one could encounter a different – and hypothetically more reliable – news environment. For example, salient events, such as the Covid-19 pandemic, have a highly saturated news environment. On the one hand, substantial reporting from reliable sources on this topic are available, which could reduce the effect of SOTEN on belief in misinformation. On the other hand, it is possible that highly salient events also attract more misinformation, for either political or economic reasons (Munger, 2020). To determine whether the effect of SOTEN on belief in misinformation holds when researching misinformation about a salient event, we ran a fourth study (Study 4), similar to Studies 2 and 3 but which included only the most popular articles whose central claim covered the health, economic, political, or social effects of Covid-19. For this study, which ran over 8 days in June 2020, we recruited 386

[20] For the full regression table see Section B of the Supplementary Materials.

respondents through Qualtrics.[21] Respondents were presented with at least one false/misleading online Covid-related article within 72 hours of publication.[22] Row 4 of Figures 1a and 1b presents the treatment effect from Study 4 using the categorical and ordinal scale. We find remarkably similar results relative to the first three studies: searching online increases the probability that a respondent rates a false/misleading article as true by 0.067 (P=0.0451, Cohen's D = 0.14), or an increase in belief in misinformation of 20% and an increase by 0.26 on a 7-point ordinal scale (P=0.0054, Cohen's D = 0.14).[23]

Taken together, Studies 1–4 present consistent evidence across a variety of experimental designs, time periods, and topics that SOTEN increases belief in misinformation. This search effect is concerning on its own, but to better understand the role of search engines and to inform evidence-based interventions, it is important we evaluate the mechanism. In the following section, we explore one such possible mechanism—exposure to unreliable information corroborating the initial misinformation that was viewed—for why SOTEN increases belief in misinformation.

Can Exposure to Unreliable Information Explain Why SOTEN Increases Belief In Misinformation?

The theory of "data voids" suggests that when individuals search online about misinformation, especially misinformation around breaking or recently published news, search engines may return little credible information, instead placing non-credible information at the top of results (Golebiewski and boyd, 2019). These data voids likely exist for a variety of reasons. First, unreliable news publishers often use terms to guide users to these data voids, where only one point of view is represented (Golebiewski and boyd, 2019).[24] Second, unreliable news sources often re-use stories from each other, polluting search engine results with other similar non-credible stories. Benkler et al. (2018) argue that the media dynamics in the United States (particularly on the right) "tend

[21] Details about these articles can be found in Section A3 of the Supplementary Materials.

[22] Relative to Studies 1-3, we delayed sending the articles to respondents by 24 hours. We did so in order to immediately communicate the fact-checker evaluations after completion of the survey, thus minimizing any potential risk of misinforming respondents about the pandemic.

[23] For the full regression table see Section B of the Supplementary Materials.

[24] Golebiewski and boyd (2019) analyze how unreliable news sites leverage search engine optimization techniques and encourage readers to use specific search queries when searching online by consistently using a distinct phrase in their stories and in other media.

to reinforce partisan statements, irrespective of their truth" (Page 75). This "propaganda feedback loop" creates a network of news outlets reporting the same misinformation and thus flooding search engine results with false but seemingly corroborating information. The topics and framing of false/misleading news stories are also often distinct from those covered by mainstream outlets, which limits the amount of reliable news sources to be returned by search engines when searching for supporting information about these stories. Finally, direct fact-checks may be difficult to find given that most false narratives are never fact-checked at all and, for stories that are evaluated by organizations such as Snopes or PolitiFact, these fact-checks may not be posted in the immediate aftermath of a false article's publication. As a result, it would not be surprising that exposure to unreliable news is particularly prevalent when searching online about recently published misinformation.

To investigate the prevalence and effect of exposure to unreliable information while searching for information online, Study 5 combines survey data with digital trace data. In this final randomized controlled trial (between-respondent study), we collect articles using the same article selection protocol, and, as in Study 1, asked two different groups of respondents to evaluate the same false/misleading or true articles within 72 hours of publication and in the same 24-hour window. The treatment group was required to search online using Google before providing their assessment of the article's veracity, whereas the control group was not. For those in the treatment group, we collect the URLs they visit and the top ten Google search engine results to which they were exposed by means of a custom-made browser plug-in that respondents consented to install. Over this twelve-day study, we recruited 1,677 respondents living in the United States through Amazon's Mechanical Turk and presented them with three highly popular articles from mainstream and low-quality sources within 72 hours of publication.[25] Over the course of this study, 17 false/misleading articles were evaluated by individuals in the control (871 evaluations from 615 unique respondents) and treatment group (608 evaluations from 451 unique respondents).[26] By asking respondents in both the control and treatment group to install a custom web extension that collected their web browsing behavior, we were able to collect digital trace data associated with 73% of evaluations of false/misleading articles in the treatment group and 91% of evaluations of false/misleading articles

[25]More details about the respondent recruitment, the article selection, and how we determined the veracity of each article can be found in the Methods section.

[26]Details about these articles can be found in Section A4 of the Supplementary Materials.

in the control group. This difference in compliance rates can be explained by the difference in the web extension for the treatment group relative to the one given to the control group. For technical reasons related to capturing HTML, the respondents in the treatment group had to wait at least five seconds for the web extension that was installed to collect their Google search engine results, which may have resulted in some respondents accidentally removing the web extension. If they did not wait for five seconds on a Google search results page, the extension would turn off and they would have to turn it back on. These instructions were presented clearly to the respondents, but likely resulted in differences in compliance. We still collected the survey results for all respondents regardless of compliance and used these responses for the analyses in Figure 2b. We only exclude non-compliant responses from our analysis when we analyze the effect of the quality of searching engine results. We exclude all non-compliant respondents in these analyses to limit possible selection effects, but these respondents were included in all other analyses. More details on compliance in the treatment and control group can be found in the Methods section, but for most demographic characteristics (age, gender, income, and education), we did not find any meaningful statistically significant evidence of differences between compliers and non-compliers in the treatment and control groups. Across both groups, we did find that compliers were more likely to self-identify as liberal by about 0.8 on a 7-point scale (F=23.917, P<0.0001) and more likely to self-report higher levels of digital literacy.[27]

Figure 2a presents the proportion of search queries among those in the treatment group about true and false/misleading articles that return at least one unreliable news source in their Google search engine results. To assess the reliability of a news source, we use classifications from the NewsGuard service available at the time of the study (August 2021).[28] A histogram of NewsGuard scores for the majority of online news domains can be found in Section C of the Supplementary Materials.[29] Figure 2a shows that search queries about true articles are much less likely to return unreliable news among search results than search queries about false/misleading articles. Only 16%

[27]More details on this difference in means testing can be found in the Methods section at the end of the paper.

[28]Newsguard is an internet plug-in that informs users if a site they are viewing is reliable. NewsGuard employs a team of trained journalists and experienced editors to review and rate news and information websites based on nine criteria. The criteria assess basic practices of journalistic credibility and transparency, assigning a score from 0 to 100. Sites with a score below 60 are deemed as unreliable, and those above 60 are reliable. NewsGuard has ratings for over 5,000 online news domains, which is responsible for about 95% of all the news consumed in the United States, United Kingdom, France, Germany and Italy. More information can be found here: https://www.newsguardtech.com. A sample of their ratings can be found here: https://www.newsguardtech.com/ratings/sample-nutrition-labels/.

[29]The full list of online news domains and their ratings is licensed by NewsGuard to approved researchers.

of individuals are exposed to at least one unreliable news link when they search about true articles, whereas 38% of individuals are exposed to at least one unreliable news link when they search about false/misleading news.[30]

Using evaluations from Study 5, we first measure the effect of searching online on belief in false articles. In Figure 2b we present the treatment effect (encouraged to search online) on the probability of believing misinformation using both a dichotomous outcome (rating a false/misleading story as true: 1=Yes ; 0=No), a 7-point ordinal scale of veracity, and a 4-point ordinal scale.[31] Like the previous four studies, we find that those who search online about misinformation were more likely to believe misinformation than those who did not. We find that the effect of SOTEN is larger than in the previous studies, likely because the treatment is stronger in this study relative to the others.[32] In this final study, searching online increased the probability a respondent rated a false or misleading article as true by 0.107 (P=.0143, Cohen's $D = 0.21$), which is larger than the effect observed in previous studies. Searching online also increased the average score by 0.16 (P=0.0434, Cohen's $D = 0.16$) on a 4-point ordinal scale, but not on a 7-point ordinal scale (P=0.2155, Cohen's $D = 0.10$).

Using digital trace data collected through the custom browser plug-in, we were able to measure the effect of SOTEN on belief in misinformation by those exposed to unreliable and reliable information by search engines. To this end, we measured the effect of being encouraged to search online on belief in misinformation for our control group and two subsets of the treatment group: those who were exposed to Google search engine results that returned low quality results (defined as at least 10% of links coming from low quality news sources)[33] or high quality (defined as the first ten links coming only from very reliable news sources).[34] Half of all evaluations in the treatment group fit in either of these two subsets.[35] Across these two subsets, Figure 2c shows that

[30]We run this same analysis excluding the original article from the search engine results and we find that only 11% of individuals are exposed to at least one unreliable news link when they search about true articles, whereas 28% of individuals are exposed to at least one unreliable news link when they search about false/misleading news. Figures 2A, 2C, and 2D are replicated excluding the original article from the search engine results in Section S of the Supplementary Materials. Similar results are reported.

[31]For the full regression table see Section B of the Supplementary Materials.

[32]In Study 5, respondents were asked to travel to a Google search engine to search online to be fully compensated, and the custom browser plug-in enabled us to confirm compliance. In Studies 1-4, we could not verify whether respondents complied with our search encouragement.

[33]Newsguard considers sites with a rating of 60 or below (out of 100) as unreliable.

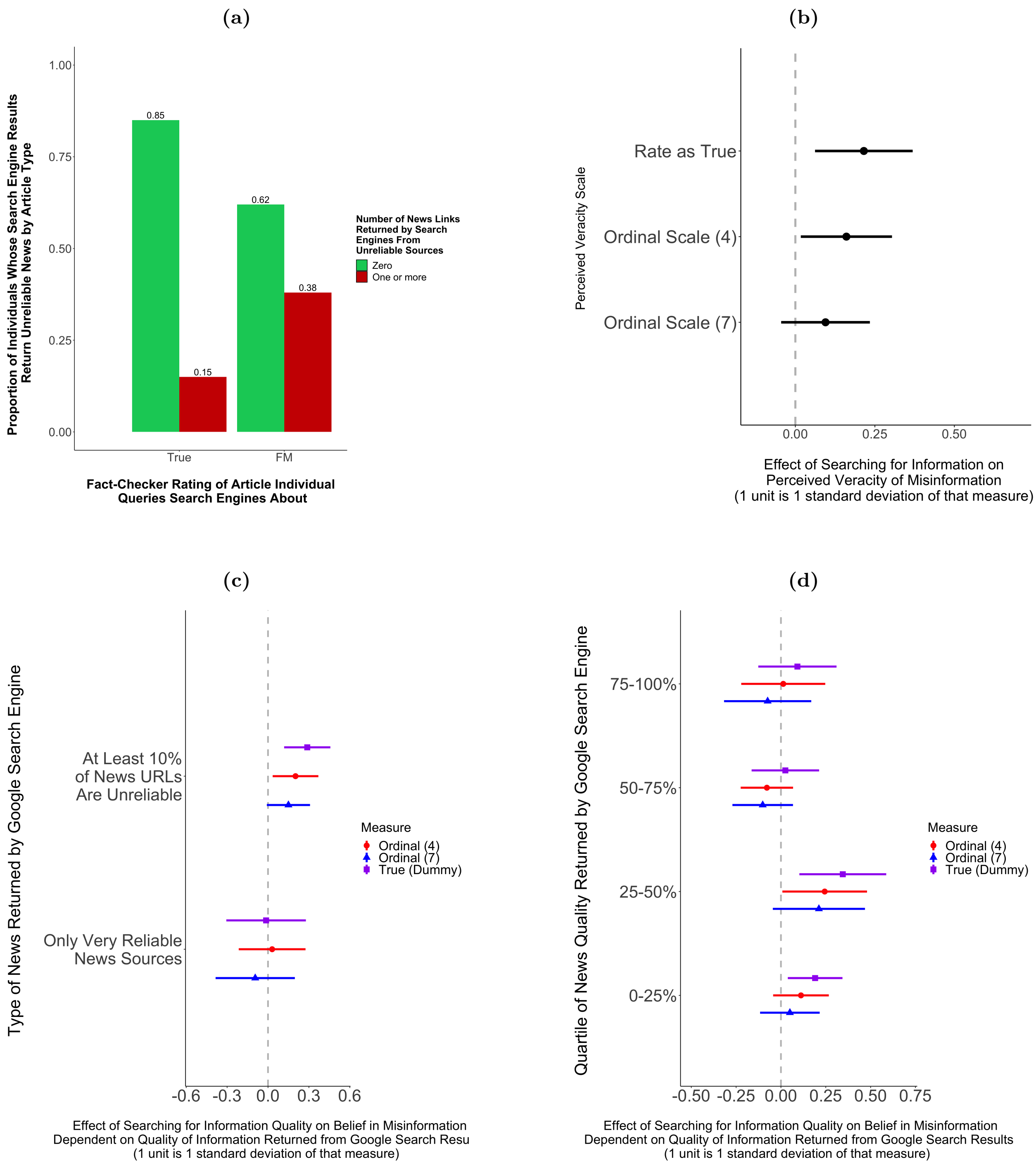
[34]News sites are considered very reliable if they are given a score of 85 or higher by NewsGuard.

[35]11.7% of the 461 evaluations fit in the "some unreliable news" group and 30.0% of the 498 evaluations fit in the very reliable news sites group. Although subsetting the data in this way ignores 58% of the treatment group, we

the probability an individual believes misinformation is substantially higher than the control group among respondents who are exposed to at least one unreliable news site, but it is not higher among those in the treatment group who are only exposed to very reliable news sites. Together, these results are consistent with the theory that lower quality search engine results can increase belief in misinformation by returning low-quality results. As further evidence, in Figure 2d we use the entire sample and calculate the probability of rating misinformation as "true" by quartile of the mean news quality across the top ten links returned by Google during the evaluation, leading to similar results. Figure 2c shows that respondents who are exposed to search engine results with the lowest quality news are more likely to believe misinformation than those who are exposed to higher quality news, suggesting that exposure to unreliable news may explain why SOTEN increases belief in misinformation. In addition, we find that respondents who search online about misinformation and are exposed to the highest quality information are no more likely to believe misinformation than those in the control group. To be clear, the information returned by Google is post-treatment, so this analysis does not infer a causal relationship (Montgomery et al., 2018), but it provides evidence consistent with the theory that low-quality information returned by search engines explains the search effect we identify. If our explanation is indeed correct and exposure to low quality search results is associated with belief in misinformation, it remains unclear why certain individuals are exposed to low-quality news sources while others are not. In the next section, we investigate the search terms individuals use to see if this is associated with exposure to low-quality results. More specifically, we consider whether evidence from our work is consistent with two plausible interpretations for why individual's use search terms that are more likely to return low-quality information: digital literacy and ideological congruence with the ideological perspective of the misinformation.

are interested in the effect of search among groups exposed to very different levels of information quality. Our next analysis looks at the whole set of responses.

Figure 2: How Does News Returned in Google Search Results affect belief in misinformation? (Study 5). Panel a presents the proportion of individuals who when searching online about an article are exposed to different levels of unreliable news sites by the Google search engine. We present these proportions for those searching about true articles and those searching about false/misleading articles. Panel b presents the effect sizes and 95 percent confidence intervals for linear regression models testing the effect of searching online during Study 5 respectively as a unit of the standard deviation of the dependent variable. Subset by the quality of news returned in their search engine results, Panel c and d present these same marginal effects.



Why Are Individuals Exposed to Unreliable Information In Their Search Results?

In this section, we assess the viability of two possible explanations for why individuals are exposed to low-quality news in their search results: (1) ideological congruence and (2) low levels of digital literacy. In the ideological congruence account, partisans may seek out, either consciously or not, information from ideologically congruent sources through the use of search terms that reflect their ideological perspective (Peterson and Iyengar, 2021). Relatedly, previous work has found that search engine results for political search queries can be personalized to individual-level characteristics and so the user's ideology may lead to more information that aligns with their ideological worldview (Robertson et al., 2018), possibly amplifying the impact of ideological congruence (Hu et al., 2019). This may lead to a concentrated exposure among those ideologically congruent to the misinformation about which they are searching. To this end, we investigate whether exposure to low-quality search results is concentrated among respondents whose self-reported ideology aligns with the ideological slant of the misinformation. Another possible explanation is that individuals with low levels of digital literacy are more likely to fall into these data voids. Previous research has found that individuals with higher levels of digital literacy use better online information searching strategies (Atoy Jr et al., 2020). This suggests that those with lower levels of digitally literacy may be more likely to use search terms that lead to exposure to low-quality search results.

To assess the empirical support for these two potential explanations, we begin by exploring which individual level characteristics are associated with exposure to unreliable news by fitting an OLS regression model with article-level fixed effects and standard errors clustered at the respondent and article level to predict exposure to unreliable news site in search results. We include basic demographic characteristics (income, education, gender, and age) in the model. Figure 3a presents the effect of a one standard deviation increase of each variable on the probability of being exposed to at least one unreliable news story in the search engine results when SOTEN. Evidence from these results suggest that lower levels of digital literacy and ideological congruence correlates with exposure to unreliable news in search results after conditioning on demographic characteristics. A standard deviation increase in digital literacy decreases the probability of being exposed to an unreliable news source in their Google search engine results by 0.034 (P=0.14). A standard deviation increase in ideological congruence appears to increase the probability of being exposed to unreliable news by a Google search engine by 0.037 (P=0.082).

Individuals with lower levels of digital literacy may be more likely to be exposed to unreliable information because of what they actually type into search engines. To investigate the effect of search terms on the reliability of news returned by the Google search engine, we collected all of the search terms used by individuals in the treatment group. The "data voids" theory supposes that if one uses search terms unique to misinformation, one is more likely to be exposed to low-quality information. To determine if this affects the quality of search engine results, we coded all search terms for whether they contained the headline or URL of the false article. We find that this is indeed the case. Roughly 9% of all search queries that individuals entered were the exact headline or URL of the original article, and Figure 3b shows that those who use the headline/lede or the unique URL of misinformation as a search query are much more likely to be exposed to unreliable information in the Google search results. 77% of search queries that use the headline or link of a false/misleading article as a search query return at least one unreliable news link among the top ten results, whereas only 21% of search queries not using the headline or URL of an item of misinformation return at least one unreliable news link among the top ten results.[36]

To determine who is most likely to use headlines or URLs as their search query, we fit an OLS regression model with article-level fixed effects and standard errors clustered at the respondent and article level to predict using the headline or URL as a search term, again conditioning on basic demographic characteristics. Figure 3c presents the results of this model and shows that those with lower levels of digital literacy are more likely to use the headline or the unique URL of the false article as their search query when SOTEN, conditioning on ideological congruence and demographics. A standard deviation increase in digital literacy decreases the probability of using the headline or the unique URL of the false article as their search query by 0.034 (P=0.016).

Using the headline/lede as a search query likely produces unreliable results because they contain distinct phrases that only producers of unreliable information use. Golebiewski and boyd (2019) find that manipulators create content that dominates the search engine environment for people

[36]We run this same analysis excluding the original article from the search engine results and the effect holds. 57% of search queries that use the headline or link of a false/misleading article as a search query return at least one unreliable news link among the top ten results, whereas only 18% of search queries not using the headline or URL of an item of misinformation return at least one unreliable news link among the top ten results.

who use certain search terms. An investigation of the search terms used by individuals and the quality of news sources they are exposed to for one article in Study 5 appears to support this line of reasoning. Specifically, we analyzed the search terms for those searching online about the false/misleading article titled: "U.S. faces engineered famine as COVID lockdowns and vax mandates could lead to widespread hunger, unrest this winter." The term "engineered famine" in the article is a unique term unlikely to be used by reliable sources. An analysis of respondents' search results finds that by adding the word "engineered" in front of "famine" changes the search results returned. 0% of search terms that contained the word "famine" without "engineered" in front of it returned unreliable results, whereas 63% of search queries that added "engineered" in front of the word "famine" were exposed to at least one unreliable result. In fact, 83% of all search terms that returned an unreliable result contained the term "engineered famine."[37]. Over half (52%) of the respondents that used "engineered famine" in their search term were ideologically congruent to the ideological perspective of the misinformation, whereas less than a quarter of respondents (23%) who just used "famine" without "engineered" in front of it were ideologically congruent to the ideological perspective of the misinformation. There is very little difference in the average digital literacy of these groups.

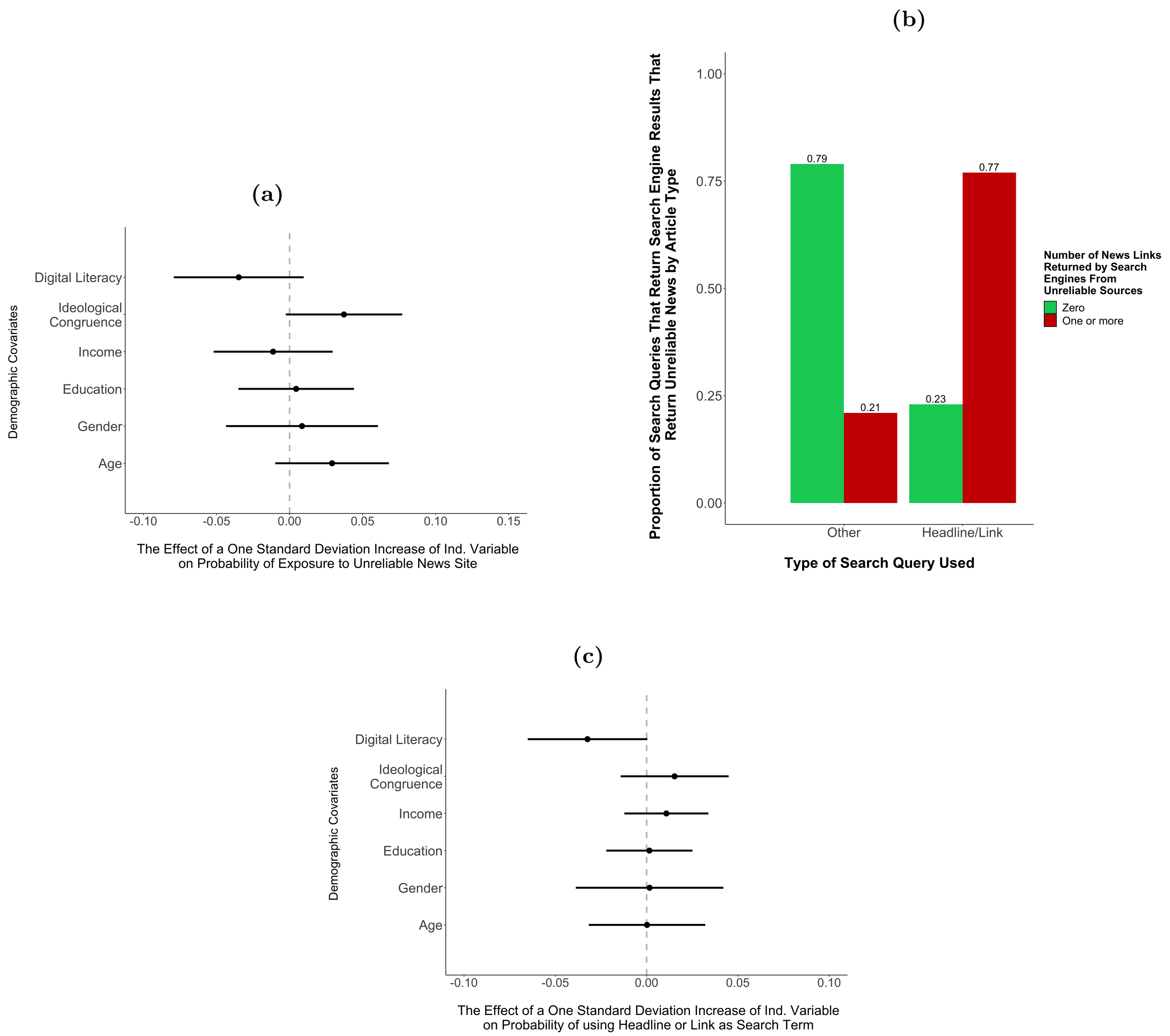
The Impact of Search on Belief in True News

Although the finding that SOTEN increases belief in misinformation is concerning in isolation, to fully evaluate the effect of recommending individuals to search online, we must also measure the search effect on belief in true news. We pre-registered a hypothesis that searching online would also increase belief in true news and find support for this hypothesis in Studies 1–5. During our first study (Study 1), a between-respondent study, we collected 4,290 evaluations of 49 false/misleading and true news articles from 1,456 unique respondents in the control group and 4,254 evaluations from 1,447 unique respondents in the treatment group.[38] Figure 4a shows that in Study 1 searching online increases the probability of correctly rating true news as true by 0.072 (P=0.0001, Cohen's D = 0.146), which is quite similar to the effect on rating false/misleading as true (0.055 ; P=0.0382,

[37]All search terms used for this article and the news quality returned by them can be found in Section W of the Supplementary Materials

[38]Details about these articles can be found in Section A1 of the Supplementary Materials.

Figure 3: Who is Exposed to Unreliable News Sites When Evaluating Misinformation Online? (Study 5). Panel a presents the predicted exposure to unreliable news sources when searching online about false/misleading news articles. Panel b presents the proportion of individuals who when searching online about a false/misleading article are exposed to different levels of unreliable news sites by the Google search engine. We present these proportions for those who use the headline of the article or the link of the article and those who use another query. Panel c presents the probability of using the headline/lede or unique URL when searching online about false/misleading news articles.



Cohen's D = 0.12). In Study 2, where we set out to test whether the search effect was strong enough to change an individual's evaluation after they had already assessed the veracity of a news story, we find that the search effect on true news is substantially weaker than in Study 1. Figure 4a shows that in Study 2, searching online increases the probability of correctly rating true news as true by only 0.0211 (P=0.083, Cohen's D = 0.044), which is small relative to the search effect on rating false/misleading as true in the same study (0.071 ; $P<0.0001$, Cohen's D = 0.15). Studies 3 and 4 also report relatively small search effects on true news. In Study 3, a within-respondents study run months after publication of the articles, searching online increased the probability of correctly rating true news as true by 0.047 (P=0.0001, Cohen's D = 0.097), which is smaller than the search effect on probability of rating false/misleading news as true in the same study (0.063 ; P=0.0034, Cohen's D = 0.14). In Study 4, a within-respondents study run strictly on articles about COVID-19, there was no statistically significant search effect on the the probability of correctly rating true news as true (0.03, P=0.165, Cohen's D = 0.062), but there was a search effect on the probability of rating false/misleading news as true in the same study (0.067 ; P=0.0451, Cohen's D = 0.21). In our final study (Study 5), a between-respondent experiment with a strict measure of compliance, we found that the search effect on the probability of rating true news as true was similar to the effect identified in Study 1, another between-respondent experiment. In Study 5, searching online increased the probability of correctly rating true news as true by 0.15 ($P<0.0001$, Cohen's D = 0.357), which is larger than the effect on rating false/misleading as true in Study 5 (0.105 ; P=0.0119, Cohen's D = 0.21). These results, as displayed in Figure 4a, show that the search effect on belief in true news is similar to the search effect on belief in false/misleading news when individuals search online before they determine the veracity of true news, but is smaller or (at times) non-existent when individuals are asked to evaluate true news after having already evaluated the true news article's veracity.

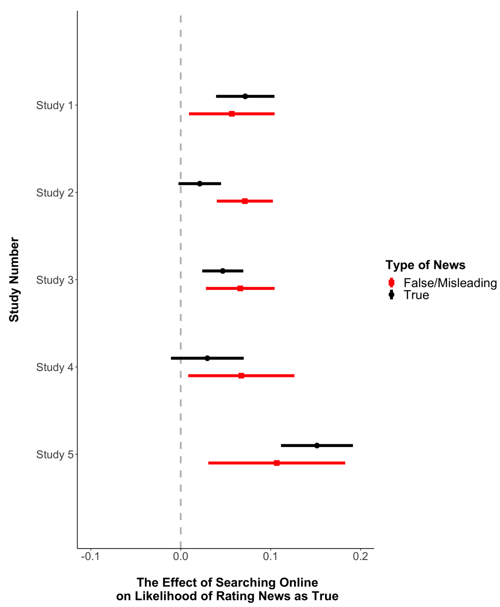
Measuring the search effect on all true news ignores that SOTEN may have heterogeneous effects depending on the quality of the source. The online news source affects whether an individual believes an article (Druckman, 2022) due to a source's reputation (Althaus and Tewksbury, 2000; Flanagin and Metzger, 2000) and the design of the website (Flanagin and Metzger, 2007; Fogg et al., 2001). It is possible that individuals may be less likely to change their perceived veracity of true news from credible sources after searching online, as the source's credibility heuristics are relatively strong. However, without receiving a strong signal of source credibility, people may be more likely to believe a true article from a low-quality source if a search engine returns similar coverage from other sources. To this end, we also subset our measurement of the search effect on true articles from mainstream (more reputable) and low-quality (less reputable) sources.

This exploratory analysis shows that the effect of SOTEN for a true article is significantly larger if the article is published by a lower-quality source than if published by a mainstream source. In fact, in four of the five studies there is only a small or non-existent search effect on the probability of rating true news as true from mainstream sources. Figure 4b shows that in Study 1 the effect of searching online is quite similar across false/misleading news and true news from both low-quality and mainstream sources. Searching online increased the probability of correctly rating true news from mainstream and low quality sources as true by 0.045 (P=0.017, Cohen's D = 0.10) and 0.105 (P=0.001, Cohen's D = 0.21) respectively. This is quite similar to the search effect on belief in false/misleading news in Study 1 (0.055 ; P=0.0382, Cohen's D = 0.12). When we turn to within-respondent experiments, we find a divergence in the search effect among true news from low-quality sources and true news from mainstream sources. Similar to Study 1, Figure 4b shows that in Study 2 searching online increases the probability of correctly rating true news from low quality sources as true by 0.081 (P=0.0001, Cohen's D = 0.16), but contrary to Study 1, we find that searching online *decreases* belief in true news from mainstream sources by 0.024 (P=0.069, Cohen's D = 0.05). Study 3 produces similar results to Study 2. Figure 4b shows that searching online increases the probability that a respondent rates a true article from a low-quality source as true by 0.122 (P<0.0001, Cohen's D = 0.25), an effect almost twice size of the the online search effect on false/misleading news in Study 3, but there was no search effect on the probability that a respondent rates a true article from a mainstream source as true (P=0.86, Cohen's D = 0.01). These results are mirrored in Study 4: Figure 4b shows that searching online increases the probability that a respondent rates a true article from a low-quality source as true by 0.85 (P=0.044, Cohen's D = 0.17), but no increase in the probability that a respondent correctly rates a true mainstream story as true (P= 0.92, Cohen's D = 0.01). Finally, Study 5, a between-respondent experiment with a stronger incentive to search, presents similar results to Study 1. Figure 4b shows that searching online increases the probability that a respondent rates a true article from a low-quality source as true by 0.23 (P<0.0001, Cohen's D = 0.50) and increases the probability that a respondent correctly rates a true mainstream story as true by 0.09 (P= 0.0008, Cohen's D = 0.24).

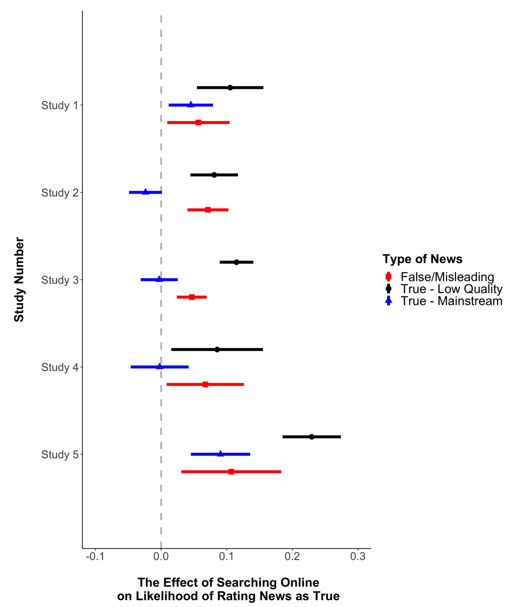
Results in Figure 4b also show that there is a clear difference in the search effect on true news from low quality and mainstream sources. This difference is most pronounced in within-respondent experiments. To further demonstrate the difference in between-respondent and within-respondent experiments, Figure 4c presents the search effect when we pool all evaluations of true news (from low-quality and mainstream sources) and false/misleading news articles by experiment type (within-respondent and between-respondent) and re-run the same analysis used to produce the effect sizes in Figure 4a. In between-respondent experiments, the search effect on belief in true news from mainstream sources is similar to that of false/misleading articles, while the search effect on belief in true news from low-quality sources is larger than the others. In within-respondent experiments, we do not report any search effect on belief in true news from mainstream sources, and the search effect on belief in true news from low-quality sources is slightly larger than the search effect on belief in false/misleading articles.

Figure 4: The effect of searching online to evaluate news on belief in false/misleading and true news. Panel a presents the effect sizes and 95 percent confidence intervals for linear regression models testing the effect of online search on rating true news as true and false/misleading news as true during Studies 1-5. Panel b presents the effect of online search on rating true news as true from low-quality sources, true news as true from mainstream sources, and false/misleading news as true during Studies 1-5. Panel c presents the effect of online search on rating true news as true from low-quality sources, true news as true from mainstream sources, and false/misleading news as true for between-respondent experiments (Studies 1 and 5) and within-respondent experiments (Studies 2-4).

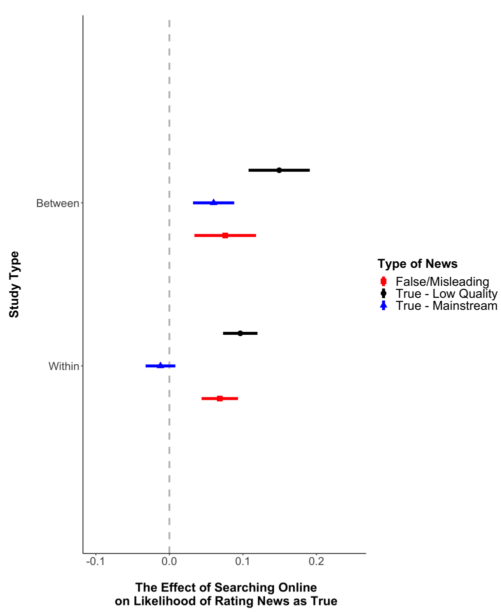
(a)



(b)



(c)



The results presented in Figures 4a-4c show that the effect of online search on true news is much larger if the article is published by a low-quality source than if published by a mainstream source. In fact, the effect of SOTEN about a true story from a low-quality source is often similar to or even surpasses the search effect for false articles, and the effect of SOTEN for true news from mainstream sources is either small or non-existent. It is possible we do not measure much of an effect of SOTEN on belief in true news from mainstream sources, because of a ceiling effect. Many of our respondents in the control group (Those not encouraged to search for information online.) already rate true news from mainstream sources correctly as "true" (between 65-80% across all five studies). Taken together, these heterogeneous effects across false and true news articles paint a comprehensive and complex picture of the online search effect.

Discussion

While prior research has explored the role of social media in the diffusion of misinformation, we know relatively little about the impact of search engines, an integral but understudied piece of the digital information ecosystem. Across five studies, we find that the act of searching online to evaluate news *increases* belief in highly popular misinformation by measurable amounts. This result is consistent and robust across four different contexts: (1) between-respondent and within-respondent experiments (2) using general misinformation and misinformation about a salient event (the Covid-19 pandemic), (3) within 72 hours of publication and months after publication (4) using respondents recruited by Qualtrics and respondents recruited on Mechanical Turk. In our fifth study, which applies the strongest treatment, encouraging individuals to SOTEN increased the probability of rating misinformation as true by 0.105. Other studies with slightly weaker SOTEN encouragements also report similarly large increases in belief in misinformation.

To better understand our initial findings in Studies 1–4 and identify potential remedies, we assessed the relative importance of the quality of information returned by search engines in increasing belief in misinformation. Using digital trace data collected by a custom browser plug-in, we provide novel evidence of the existence of data voids and find that when individuals search online about misinformation, they are more likely to be exposed to lower quality information than when individuals search about true news. Importantly, this exposure may matter: those who are exposed to low-quality information are more likely to believe misinformation relative to those who are not. We then find that there are two possible explanations for why exposure to more low quality information might make people more likely to believe false news stories: ideological congruity and digital literacy. Those who are ideologically congruent to the perspective of the false article and those with low levels of digital literacy are more likely to be exposed to lower-quality information when SOTEN. Finally, we find evidence that SOTEN increases belief in true news from low-quality sources, but inconsistent evidence of the effect of SOTEN on belief in true news from mainstream sources. While practitioners and policymakers must balance the heterogeneous effects of SOTEN across article veracity and source quality, we think the increase of belief in misinformation should be of particular import when designing digital media literacy interventions.

To be clear, there is a related dynamic that is worthwhile to study, but is not fully captured in this design: namely, online users have full discretion, often without encouragement, around which stories or topics to evaluate through online search. While this process should be the subject of future research that builds on what we have learned here, it is the case that our current study captures the impact of the intended effect of numerous digital media literacy guides. More specifically, the digital media literacy guides previously cited aim to expand the use of online search engines to evaluate the veracity of news, with the explicit goal of reducing belief in misinformation. However, the impact of search has yet to be established, and so while our design does not perfectly capture the effect of disseminating this recommendation "in the wild," our results indicate the likely effect of the intervention if it were adopted. Ultimately, we measure how beliefs in false/misleading and true articles change when respondents search online compared to when they do not. This allows us to properly measure the effect searching online has on belief in false/misleading and true news stories. While our pre-registered analysis focuses on the treatment groups who were encouraged to search, we also have exploratory analysis using control group data that more closely speaks to the search effect when people have full discretion over what to search. Using these data, we find a similar effect: people who, without encouragement, searched to evaluate misinformation were more likely to believe it (see Section V in the Supplementary Materials). Future work could consider using observational data to measure the behavioral impact of disseminating digital media literacy guides, but we think that a better understanding of the impact of SOTEN is a key first step.

In addition to this limitation, we do not allow individuals to select into the news that they would normally read. Allowing this self-selection in communication studies can be of particular importance, because we would like to determine the effect of search on news articles individuals in our study actually read outside of the laboratory (Gaines and Kuklinski, 2011). Indeed, studies that may not allow for this self-selection do not correctly identify heterogeneity of effects across individuals. In our case, we believe exposing individuals to highly popular articles that are widely circulating on social media in the period of most likely exposure properly captures the pattern of online consumption of news. Individuals on social media are likely becoming less habitual about their news consumption and becoming more likely to be exposed to viral news on their social media feeds that no longer solely present individuals with what their friends are sharing. Given this shift in online news consumption patterns, we believe measuring the search effect on highly popular articles and not allowing individuals to self-select into articles is not a shortcoming of our design.

The QAnon movement recommends that people "do the research" themselves (Marwick and Partin, 2020), which seems like a counter-intuitive strategy for a conspiracy theory oriented movement. Our findings, however, suggest that the strategy of pushing people to verify low-quality information online might paradoxically be even more effective at misinforming them. For those who wish to learn more, they risk falling into data voids—or informational spaces where there is plenty of corroborating evidence from low-quality sources—when using online search engines, especially if they are doing "lazy searching" by cutting and pasting a headline or URL. Ironically, media literacy guides also place an emphasis on doing your own research. Our findings highlight the need for media literacy programs to ground their recommendations in empirically tested interventions, as well as search engines to invest in solutions to the challenges identified here. For example, recent developments in the space — such as the expansion of teaching lateral reading strategies (Breakstone et al., 2021) and Google's warning when no credible information is available for given search queries[39] — are interesting steps in this direction and deserve further testing.

[39] More information can be found here: https://support.google.com/websearch/answer/12395529?hl=en

Methods

In all five studies we received informed consent from all of the participants. We also excluded participants for inattentiveness. The researchers were not blinded to the hypotheses when carrying out the analyses. All experiments were randomized. No statistical methods were used to predetermine sample size.

The pre-registration for Studies 1 and 2 are available at https://osf.io/akemx/. The methods we use for all five studies are based on analysis outlined by this pre-registration. It specified that all analyses would be performed at the level of the individual item (that is, one data point per item per participant) using linear regression with standard errors clustered on the participant. The linear regression was preregistered to have a belief in misinformation dummy variable (1 = false/misleading article rated as "True", 0 = article rated as "false/misleading" of "could not determine") as the dependent variable and the following independent variables: treatment dummy (1= treatment group ; 0=control group) , education (1=No High School degree ; 2=High School degree ; 3= Associates Degree ; 4=Bachelors Degree ; 5=Masters Degree ; 6=Doctorate Degree), age, income (0=$0 - $50,000 ; 1=$50,000 - $100,000 ; 2=$100,000 - $150,000 ; 3=$150,000 plus), gender (1=self-identify as female,0=self-identify as not female.), and ideology (-3=Extremely Liberal ; -2=Liberal ; -1=Slightly Liberal ; 0=Moderate ; 1=Slightly Conservative ; 2=Conservative ; 3=Extremely Conservative).[40] We also stated that we would repeat the main analysis using 7-point ordinal form (1: definitely false to 7 definitely true) in addition to our categorical dummy variable. Our key prediction stated that the treatment—encouraging individuals to search online—would increase belief in misinformation, which is the hypothesis tested in this study.

However, such an analysis does not account for the likely heterogenous treatment effect across articles evaluated or whether the respondent was ideologically congruent to the perspective of the article. Given this, we deviated from our pre-registered plan on two distinct points: (1) to control for the likely heterogeneity in our treatment effect across articles, we add article fixed effects and cluster the standard errors at the article-level (Abadie et al., 2017) in addition to the individual-level; (2) We also replace the ideology variable with a dummy variable that accounts for whether an individual's ideological perspective is congruent with the article's perspective. Given that it

[40] For a full description of our variables used in Studies 1-4 and Study, see Sections I and J of the Supplementary Materials.

is whether one's ideological perspective is congruent to the piece of misinformation, not ideology in and of itself that affects belief in misinformation, we think this is the proper variable to use. Although we deviate from these aspects of the pre-registered analysis, results for Studies 1-4 using this pre-registered model can be found in Section O of the Supplementary Materials. The results from these models more strongly support the hypothesis than the results we present in the main text of this paper.

Article Selection Process

To distribute a representative sample of highly popular news articles directly after publication to respondents, we created a transparent, replicable, and pre-registered article selection process that sourced highly popular false/misleading and true articles from across the ideological spectrum to be evaluated by respondents within 24-48 hours of their publication.[41] Specifically, we sourced one article per day from each of the following five news streams: liberal mainstream news domains; conservative mainstream news domains; liberal low-quality news domains; conservative low-quality news domains; and low-quality news domains with no clear political orientation. Each day we chose the most popular online articles from these five streams that had appeared in the previous 24 hours and sent them to respondents who were recruited either through Qualtrics (Studies 1-4) or Amazon's Mechanical Turk (Study 5).[42] Collecting and distributing the most popular false articles directly after publication is a key innovation that enabled us to measure the effect of SOTEN on belief in misinformation during the period in which people are most likely to consume it. In Study 3, we used the same articles used in Study 2, but distributed them to respondents 3 to 5 months after publication.

To generate our streams of mainstream news, we collected the top 100 news sites by U.S. consumption identified by Microsoft Research's Project Ratio between 2016 and 2019.[43] To classify these websites as liberal or conservative, we used scores of media partisanship from Eady et al.

[41]In Study 4 (where we only sent articles about Covid-19 to respondents), we delayed sending the articles to respondents for an additional 24 hours to allow us to receive the assessment from our professional fact-checkers before sending the articles out to respondents. Doing so allowed us to communicate fact-checker assessments to respondents once they had completed their own assessment, thus reducing the chance of causing medical harm by misinforming a survey participant about the pandemic.

[42]See Section D of the Supplementary Materials for an explanation of our sampling technique on Qualtrics and Mechanical Turk, why we chose the services, and why we believe these results can be generalized.

[43]https://www.microsoft.com/en-us/research/project/project-ratio/

(2020), who assign ideological estimates to websites based on the URL sharing behavior of social media users: websites with a score of below zero were classified as liberal and those above zero were classified as conservative. The top ten websites in each group (liberal or conservative) by consumption were then chosen to create a liberal mainstream and conservative mainstream news feed.[44] For our low quality news sources, we relied on the list of low-quality news sources from Allcott et al. (2019) that were still active at the start of our study in November 2019. We subsequently classified all low-quality sources into three streams: liberal leaning sources, conservative leaning sources, and those with no clear partisan orientation.[45]

On each day of Studies 1, 2, and 5, we selected the most popular article from the past 24 hours—using CrowdTangle, a content discovery and social monitoring platform that tracks the popularity of URLs on Facebook pages, for the mainstream sources, and RSS feeds for the low-quality ones—from each of the five streams.[46] Articles chosen by this algorithm therefore represent the most popular credible and low quality news from across the ideological spectrum.[47] In Study 3, we used the same articles used in Study 2, but distributed them to respondents 3 to 5 months after publication. In Study 4, to test if this search effect is robust to news stories related to the Covid-19 pandemic, we only sampled the most popular articles whose central claim covered the health, economic, political, or social effects of Covid-19. During Study 4 and 5, we also added a list of low-quality news sources known to publish pandemic-related misinformation, which was compiled by NewsGuard.

Survey

In each study, we sent out an online survey that asked respondents a battery of questions related to the daily articles that had been selected by our article selection protocol, as well as a litany of demographic questions.[48] Respondents evaluated each article using a variety of criteria, the

[44] The list of the sources in each mainstream stream is provided in Section E1 of the Supplementary Materials.

[45] The list of the sources in each low-quality stream is provided provided in Section E2 of the Supplementary Materials. Explanation for how the partisanship of these sources were determined is provided in Section E3 of the Supplementary Materials.

[46] We used RSS feeds for the low quality sources instead of CrowdTangle because most low-quality sources' Facebook pages had been banned and thus were not tracked by CrowdTangle; for more on CrowdTangle, see https://www.crowdtangle.com/.

[47] The number of public Twitter posts and public Facebook group posts that contained each article in Studies 1, 2, and 3 is provided in Section G of the Supplementary Materials.

[48] While they completed the survey within the Qualtrics platform, they viewed the articles directly on the website where they had been originally published. In other studies, respondents were often only asked to evaluate the

most germane of which was a categorical evaluation question: "What is your assessment of the central claim in the article?" to which respondents could choose from three responses: (1) True (2) Misleading/False (3) Could Not Determine. Respondents were also asked to assess the accuracy of the news article on a 7-point ordinal scale ranging from 1 (definitely not true) to 7 (definitely true).[49] We ran our analyses using both categorical responses and the ordinal scale(s). To assess the reliability and validity of both measures, we predict the rating of an article on a 7-point scale using a dummy variable measuring whether that respondent rated that article as "true" on the categorical measure using a simple linear regression. We find that across each study, rating an article as true on average increases the veracity scale rating on average by 2.75 points on the 7-point scale (About 1.5 standard deviations of the ratings on the ordinal scale).[50] To ensure that responses we use were actually from respondents who evaluated articles in good faith, two relatively simple attention checks for each article were used. If a respondent failed any of these attention checks, all of their evaluations were omitted from this analysis.[51]

Determining the Veracity of Articles

One of the key challenges in this study was determining the veracity of the article in the period directly after publication. Whereas many studies use source quality as a proxy for article quality, not all articles from suspect news sites are actually false (Allcott et al., 2019). Other studies have relied upon professional fact checking organizations such as Snopes or Politifact to identify false/misleading stories from these sources (Clayton et al., 2019; Pennycook et al., 2020). However, the use of evaluations from these organization is impossible when sourcing articles in real time because we have no way of knowing whether these articles will ever be checked by such organizations. As an alternative evaluation mechanism, we hired six professional fact checkers from leading national media organizations to also assess each article during the same 24 hour period as

headline/lede, rather than the full article. Providing the full article in its online form captures how respondents are able to engage with this content online.

[49] In Study 5, we also asked respondents to evaluate articles based on a 4-point ordinal scale: To the best of your knowledge, how accurate is the central claim in the article? (1) Not at all accurate (2) Not very accurate (3) Somewhat accurate (4) Very accurate

[50] For the full regression table see Section M of the Supplementary Materials.

[51] Directly after they were asked to evaluate the article we asked two basic questions about access to the article. These questions do not depend on any ability to evaluate and only measure if they are attempting to evaluate the article that we asked them to evaluate. These attention check questions can be found in Section F of the Supplementary Materials.

respondents.[52] We use the modal response of the professional fact checkers to determine whether we code an article as true, false/misleading, or 'could not determine'. We are then able to assess the ability of our respondents to identify the veracity of an article by comparing their response to the modal professional fact checker response. In terms of inter-rater reliability among fact-checkers, we can report a Fleiss' Kappa score of 0.42 for all fact-checker evaluations of articles used in this paper.[53] Although this level of agreement is quite low, it is slightly higher than other studies that have used professional fact-checkers to rate the veracity of both credible and suspect articles using the same categorical scale our fact-checkers used (Allen et al., 2021). This low level of agreement of professionals over what is misinformation may also explain why so many respondents believe misinformation and why searching online does not effectively reduce this problem. Identifying misinformation is a difficult task, even for professionals. We also present all of the analyses in this paper using only false/misleading articles with a robust mode—which we define as any modal response of fact-checkers that would not change if one professional fact-checker changed their response—to remove articles where there was higher levels of disagreement among professional fact-checkers. These results can be found in Section N of the Supplementary Materials. We find that the direction of our results do not change when using the false/misleading articles with a robust mode, although the effect is no longer statistically significant for 2 of the 4 studies using the categorical measure and 1 of the 4 studies using the continuous measure. To determine if the search effect changes with the rate of agreement of fact-checkers, we ran an interaction model and present that results in Section T of the Supplementary Materials. We find that the search effect does appear to weaken for articles that fact-checkers most agree are false/misleading. Put another way, the search effect is strongest for articles in which there is less fact-checker agreement that the article is false, suggesting that online search may be especially ineffective when the veracity of articles is most difficult to ascertain. Although this is the case, the search effect for only false/misleading articles with a robust mode (one fact-checker changing their decision from false/misleading to true will not

[52]These professional fact-checkers were recruited from a diverse group of reputable publications (none of the publications that we ask individuals to fact-check to ensure no conflicts of interest) and paid $10.00 per article. The modal response of the professional fact checkers yielded 37 false/misleading, 102 true, and 16 indeterminate articles from Study I. Most articles were evaluated by five fact-checkers; a few were evaluated by four or six. A different group of six fact-checkers evaluated all of the articles during Study 4 and 5 relative to Study 1, 2, and 3.

[53]We had unanimous fact checker agreement on over 45% of the articles in Study I. We also report the article level agreement between each pair of fact-checkers and average weighted Cohen kappa score between each pair of fact-checkers in Section K of the Supplementary Materials. These scores are reported for the articles that were rated by five professional fact-checkers.

change the modal fact-checker evaluation) is still quite consistent and strong. These results are presented in Section N of the Supplementary Materials.

Study 1

In Study 1, we tested whether SOTEN affects belief in misinformation in a randomized controlled trial that ran for ten days. During this study we asked a two different groups of respondents to evaluate the same false/misleading or true articles in the same 24-hour window, but only one after searching online. We predicted in a pre-registered report[54] that both false/misleading and true news were more likely to be rated as true by those who were encouraged to search online. This study was approved by the New York University Committee on Activities Involving Human Subjects (IRB-FY2019-3511).

[54] Link to pre-registration: https://osf.io/akemx/

Participants and Materials

On ten separate days (November 21st, 2019 to January 7th, 2020), we randomly assigned a group of respondents to be encouraged to search online before providing their assessment of the article's veracity. Over these ten days, thirteen different false/misleading articles were evaluated by individuals in our control group who were not requested to search online (resulting in 1,145 evaluations from 876 unique respondents) and those in our treatment group who were requested to search online (resulting in 1,130 evaluations from 872 unique respondents). The articles used during this study can be found in Section A1 of the Supplementary Materials.

Procedure

Participants in both the control (not encouraged to search for additional information) and treatment group were given the following instructions at the beginning of the survey: "In this survey you will be asked to evaluate the central claim of three recent news articles."[55] We then presented participants with three of five articles selected that day randomly (no articles could be shown to a respondent more than once). For each article, respondents in each group were asked a series questions about the article, such as whether it is an opinion article, does the article interest you, and how reliable is the source. Those in the control group were presented with the veracity questions most relevant to this study: "What is your assessment of the central claim in the article?" with the following options: (1) True: The central claim you are evaluating is factually accurate. (2) Misleading and/or False: Misleading: The central claim takes out of context, misrepresents, or omits evidence. ; False: The central claim is factually inaccurate. (3) Could Not Determine: You do not feel you can judge whether the central claim is true, false, or misleading. They were also asked a 7-point ordinal scale veracity question: Now that you have evaluated the article, we are interested in the strength of your opinion. Please rank the article on the following scale: 1 - Definitely Not True ; 2 ; 3 ; 4 ; 5 ; 6 ; 7 - Definitely True. Differing from the control group, participants in the treatment group (encouraged to search for additional information) were given instructions before these two veracity questions (see below). These instructions encouraged them to search online and asked the respondents questions about their search online.

Instructions To Find Evidence To Evaluate Central Claim

[55] We define the central claim as a factual statement related to the article's main point or purpose.

The purpose of this section is to find evidence from another source regarding the central claim that you're evaluating. This evidence should allow you to assess whether the central claim is true, false, or somewhere in between. Guidance for the finding evidence for or against the central claim you've identified:

(1) By evidence, we mean an article, statement, photo, video, audio, or statistic relevant to the central claim. This evidence should be reported by some other source than the author of the article you are investigating. This evidence can either support the initial claim or go against it.

(2) To find evidence about the claim, you should use a keyword search on a search engine of your choice or within the website of a particular source you trust as an authority on the topic related to the claim you're evaluating.

(3) We ask that you use the highest quality pieces of evidence to evaluate the central claim in your search. If you cannot find evidence about the claim from a source that you trust, you should try to find the most relevant evidence about the claim you can find from any source, even one you don't trust.

For additional instructions explaining how to find evidence please click this text.[56]

<u>We then presented respondents with the following four questions:</u>

(1) What are the keywords you used to research this original claim? If you searched multiple times, enter just the keywords you used on your final/successful search. If you used a reverse image search, please enter "reverse image search" in the text box.

(2) Which of the following best describes the highest quality evidence you found about the claim in your search?[57]

(3) Evidence Link: Please paste the link for the highest quality evidence you found (Paste only the text of the URL link here. Do not include additional text from the webpage/article, etc.). If you did not find any evidence, please type the following phrase in the text box below: "No Evidence."

(4) Additional Evidence Links: If you use other different evidence sources that are particularly helpful, please paste the additional sources here.

After they read the instructions and were asked these questions about their online search, those

[56] These additional instructions can be found in Section H of the Supplementary Materials.

[57] Possible responses: (A) I found evidence from a source that I trust. (B) I found evidence, but it's from a source that I don't know enough about to trust or distrust. (C) I found evidence, but it's from a source that I don't trust. (D) I did not find evidence about this claim.

in the treatment group were presented with the two veracity questions of interest (categorical and 7-point ordinal scale). In both the control and treatment conditions, the response options were listed in the same order as they are listed in this Methods section.

1 Analysis Plan

This analysis was pre-registered here https://osf.io/akemx/.

Balance Table

Below we create a balance table comparing basic demographic variables among respondents in the control and treatment group. Table 1 shows that respondents were similar across demographic variables, except for income. Those in the control group self-reported making higher levels of income than those in the treatment group. We did not record the data for 83.2% of those who entered the survey and were in the control group and 85.8% of those in the treatment group. The majority of respondents dropped out of the survey at the beginning. About 66% of all respondents who entered the survey refused to consent or did not move past the first two consent questions. So, of all respondents who moved past the consent questions, 51% of respondents dropped out of the survey in the control group and 58% of the respondents dropped out of the survey in the treatment group. About 11% of those who did not complete the survey did not because they failed the attention checks and were removed from the survey.

Balance Table

Table 1: Balance Table for Those in the Control and Treatment Group in Study 1

Demographic	Average (Treatment)	Average (Control)	Difference
Education	2.32	2.38	-0.06
Age	45.12	46.26	-1.14
Gender	0.47	0.5	-0.03
Income	0.78	1.1	-0.32***
Ideology	-0.08	0	-0.08

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Study 2

Study 2 ran similar to Study 1, but over 29 days between November 18, 2019 and February 6, 2020. In each survey that was sent in Study 1, we asked respondents in the control group to evaluate the third article they receive a second time, but only after looking for evidence online (using the same directions to search online that participants in Study 2 received).

This study measures the effect of searching online on belief in misinformation, but instead of running a between-respondent random control trial, we run a within respondent study. In this study, participants first evaluate articles without being encouraged to search online. Then, they are encouraged to search online to help them re-evaluate the article's veracity. This like a more difficult test of the effect of searching online, as individuals have already anchored themselves to their previous response. Literature on confirmation bias leads us to believe that new information will have the largest effect when individuals have not already evaluated the news article on its own. Therefore, this study allows us to measure if the effect of searching online is strong enough to change an individual's evaluation of a news article after they have evaluated the article on its own. We did not pre-register a hypothesis, but we did pose this as an exploratory research question in the registered report for Study 1.[58] This study was approved by the New York University Committee on Activities Involving Human Subjects (IRB-FY2019-3511).

Participants And Materials

During Study 2, 33 false or misleading unique articles were evaluated and re-evaluated by 1,054 respondents. We then compared their evaluation before being requested to search online and their evaluation after searching online. You can find the articles used during this experiment in Section A2 of the Supplementary Materials. Summary statistics for all respondents in this study are presented in Table 2.

Procedure

Similar to Study 1, respondents initially evaluated articles as if they were in the control group, but after they finished their evaluation they were then presented with this text: "Now that you have

[58] Link to pre-registration: https://osf.io/akemx/

evaluated the article, we would like you evaluate the article again, but this time find evidence from another source regarding the central claim that you're evaluating." They were then prompted with the same instructions and questions as the treatment group in Study 1.

Analysis plan

This analysis was posed as an exploratory research question in the registered report for Study 1.[59]

Summary Statistics

Table 2: Summary Statistic of participants in Study 2

Demographic	Mean	Standard Deviation
Education	2.31	1.23
Age	45.44	16.2
Gender (Female)	0.5	0.5
Income	0.95	0.98
Ideology	0	1.72

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Study 3

Although no pre-analysis plan was filed for Study 3, this study replicated Study 2 using the same materials and procedure, but was run between March 16, 2020 and April 28, 2020, three to five months after the publication of each these articles. This study set out to test if this search effect remained largely the same even months after the publication of misinformation when professional fact-checks are hopefully more prevalent. This study was approved by the New York University Committee on Activities Involving Human Subjects (IRB-FY2019-3511).

Participants And Materials

33 false or misleading unique articles were evaluated and re-evaluated by 1,011 respondents. We then compared their evaluation before being requested to search online and their evaluation after searching online. You can find the articles used during this experiment in Section A3 of the

[59] Link to pre-registration: https://osf.io/akemx/

Supplementary Materials. Summary statistics for all respondents in this study are presented in Table 3.

Analysis plan

No pre-registration was filed for this study.

Summary Statistics

Table 3: Summary Statistic of participants in Study 3

Demographic	Mean	Standard Deviation
Education	2.37	1.2
Age	44.04	16.36
Gender (Female)	0.49	0.5
Income	0.95	0.95
Ideology	-0.04	1.76

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Study 4

Although no pre-analysis plan was filed for Study 4, this study extended Study 2 by asking individuals to evaluate and re-evaluate highly popular misinformation strictly about Covid-19 after searching online. This study was run between May 28, 2020 to June 22, 2020. In the article selection section, we detail the changes we made in our article selection process to collect these articles. We collected these articles and sent them out to be evaluated by respondents over eight days in June and July 2020. This study measured the effect of searching online on belief in misinformation still holds for misinformation about a salient event. The salient event we use is the Covid-19 pandemic within four months of the beginning of the pandemic in the United States. This study was approved by the New York University Committee on Activities Involving Human Subjects (IRB-FY2019-3511).

Participants And Materials

13 false or misleading unique articles were evaluated and re-evaluated by 386 respondents. We then compared their evaluation before being requested to search online (the treatment) and their evaluation after searching online. You can find the articles used during this experiment in Section A4 of the Supplementary Materials. Summary statistics for all respondents in this study are presented in Table 4.

Analysis plan

No pre-registration was filed for this study.

Summary Statistics

Table 4: Summary Statistic of participants in Study 3

Demographic	Mean	Standard Deviation
Education	2.34	1.24
Age	44.57	17.43
Gender (Female)	0.47	0.5
Income	1.03	0.99
Ideology	0.01	1.74

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Study 5

To test the effect of exposure to unreliable news on belief in misinformation, we ran a fifth and final study that combined survey and digital trace data. This study was almost identical to Study 1, but we used a custom plug-in to collect digital trace data and encouraged respondents to specifically search online using Google (our web browser plug-in could only collect search results from a Google search result page).[60] Similar to Study 1, we measured the effect of SOTEN on belief in misinformation in a randomized controlled trial that ran on twelve separate days from July 13, 2021 to November 9, 2021., during which we asked two different groups of respondents to evaluate the same false/misleading or true articles in the same 24-hour window. The treatment group was encouraged to search online, while the control group was not. This study was approved by the New York University Committee on Activities Involving Human Subjects (IRB-FY2021-5608).

Participants And Materials

Unlike the other four studies, these respondents were recruited through Amazon Mechanical Turk. Only workers within the United States (verified by IP address) and those with above a 95% success rate were allowed to participate. We were unable to recruit a representative sample of Americans using sampling quotas because of the difficulty recruiting respondents from Amazon Mechanical Turk who were willing to install a web-tracking browser extension in the 24-hour period after our algorithm selected articles to be evaluated.

[60] Study 5 was not pre-registered, because it was an exploratory analysis.

Over twelve days during Study 5, a group of respondents were encouraged to SOTEN before providing their assessment of the article's veracity (Treatment) and another group was not encouraged to search online when they evaluated these articles (Control). Twelve different false/misleading articles were evaluated by individuals in our control group who were not encouraged to search online (952 evaluations from 624 unique respondents) and those in our treatment group who were requested to search online (653 evaluations from 451 unique respondents). You can find the articles used during this experiment in Section A5 of the Supplementary Materials. We do not find statistically significant evidence that respondents who we were recruited to the control group were any different on a number of demographic variables. Table 5 presents a balance table comparing those in the treatment and control group. Only 20% of those in the control group who consented to participate in the survey dropped out of the study, while 62% of those who entered the survey and were in the treatment group dropped out of the study. There was likely a large difference in Study 5 because respondents had to wait at least five seconds for the web extension that was installed to collect their Google search engine results and this likely led to a much higher dropout rate in the treatment group. There was likely a large difference in the Study 5 because they had to wait at least five seconds for the web extension that was installed to collect their Google search engine results, likely leading to much higher dropout rate in the treatment group. This differential attrition does not result in any substantively meaningful differences between those who completed the survey in the treatment and control group as shown in Table 5.

Procedure

Participants in both the control and treatment group were given the following instructions at the beginning of the survey: "In this survey you will be asked to evaluate the central claim of three recent news articles." Those assigned to the treatment group were then asked to install a web extension that would collect their digital trace data including their Google search history. They were presented with the following text: "In this section we will ask you to install our plugin and then evaluate three news articles. To evaluate these news articles we will ask to search online using Google about each news article online and then use Google Search results to help you evaluate the news articles. We need you to install the web extension and then search on Google for relevant information pertaining to each article in order for us to compensate you." They were then presented with instructions to download and activate the “Search Engine Results Saver”, which is available at the Google Chrome store here: link to Search Engine Results Saver. Those assigned to the control group were also asked to install a web extension that collected their digital trace data, but not any search engine results. They were presented with the following text: “In this section we will ask you to install our plugin and then evaluate three news articles. You must install the extension, log in and keep this extension on for the whole survey to be fully compensated.” They were then presented with instructions to download and activate the “URL Historian”, which is available at the Google Chrome store here: link to URL Historian. Both those in the control and treatment group were asked to download and install a web extension that tracked their web behavior in order to limit varying levels of attrition across both groups, due to the unwillingness or inability of respondents to install this kind of extension. After respondents downloaded their respective web extension, the study ran identical to Study 1.

Digital Trace Data

By asking individuals to download and activate web browsers that collected their URL history and scrape their search engine results, we were able to measure the quality of news they were exposed to when they searched online. We were unable to collect this data if respondents did not search on Google, deactivated their web browser while they were taking the survey, or did not wait on a search engine result page for at least 5 seconds. Therefore, in total for the 653 evaluations of misinformation in our treatment group, we collected Google search results for 508 evaluations (78% of all evaluations). We also collected the URL history of those in the control group, but did not use this data in our analyses. For most demographic characteristics (age, gender, income, and education) we have statistically significant evidence that respondents who we were able to collect search engine results were slightly different than those who were not able to. We do find that those we were able to collect this digital trace data were more likely to self-identify as liberal by about 0.8 on a 7-point scale, more likely to self-report higher levels of digital literacy, and less likely to self-identify as female. Table 6 presents a balance table comparing compliers and non-compliers within the treatment group.

Balance Table

Table 5: Balance Table for Those in the Control and Treatment Group in Study 5

Demographic	Average (Treatment)	Average (Control)	Difference
Education	3.48	3.5	-0.02
Age	37.07	39.24	-2.17**
Gender (Female)	0.43	0.47	-0.04
Income	1.74	1.79	-0.05
Ideology	-0.38	-0.5	0.12

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 6: Balance Table: Compliers and Non-Compliers in Treatment Group

Demographic	Average (Complier)	Average (Non-Complier)	Difference
Education	3.42	3.67	-0.25**
Age	36.6	38.86	-2.26*
Gender	0.42	0.5	-0.08
Income	1.73	1.74	-0.01
Ideology	-0.61	0.19	-0.8***
Digital Literacy	55.14	49.28	5.86***

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

When we analyze the effect of the quality of online information, we only include those in the control group who kept their web extension on during the survey to limit possible selection bias effects. In the control group, 93% of the respondents evaluated a false/misleading article in the control group installed the web extension that tracked their own digital trace data throughout the whole survey. Similar to the treatment group, we do find that those for whom we were able to collect this digital trace data were more likely to self-identify as liberal by about 0.55 on a 7-point scale and more likely to self-report higher levels of digital literacy. The magnitude of these differences are modest and the direction of these differences are identical to the differences in the treatment group. Table 7 presents a balance table comparing compliers and non-compliers within the control group. We do not see large difference in how those that choose to be compliant in the control group differ from those who choose to be compliant in the treatment group. Table 8 presents a balance table comparing compliers in the treatment and control group.

Table 7: Balance Table: Compliers and Non-Compliers in Control Group

Demographic	Average (Complier)	Average (Non-Complier)	Difference
Education	3.49	3.87	-0.38
Age	39.13	42.76	-3.63
Gender (Female)	0.47	0.52	-0.05
Income	1.8	1.81	-0.01
Ideology	-0.57	-0.02	-0.55*
Digital Literacy	54.81	48.59	6.22***

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

When we compare compliant respondents in the control and treatment group, we do not find large differences across various demographic variables. Those compliant in the treatment group were slightly younger by two and a half years and slightly more likely to be male. Table 7 presents a balance table comparing compliers in the control and treatment group.

Table 8: All Respondents with Digital Trace Data in Control and Treatment Group

Demographic	Average (Treatment)	Average (Control)	Difference
Education	3.42	3.49	-0.07
Age	36.6	39.13	-2.53***
Gender	0.42	0.47	-0.05*
Income	1.73	1.8	-0.07
Ideology	-0.61	-0.57	-0.04
Digital Literacy	55.14	54.81	0.33

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Data availability

Data and materials for all of the studies are available at https://github.com/SMAPPNYU/Do_Your_Own_Research.

Code availability

Code for all of the studies is available at https://github.com/SMAPPNYU/Do_Your_Own_Research.

References

Abadie, A., Athey, S., Imbens, G. W., & Wooldridge, J. (2017). *When should you adjust standard errors for clustering?* (Tech. rep.). National Bureau of Economic Research.

Allcott, H., & Gentzkow, M. (2017). Social media and fake news in the 2016 election. *Journal of economic perspectives*, *31*(2), 211–36.

Allcott, H., Gentzkow, M., & Yu, C. (2019). Trends in the diffusion of misinformation on social media. *Research & Politics*, *6*(2), 2053168019848554.

Allen, J., Arechar, A. A., Pennycook, G., & Rand, D. G. (2021). Scaling up fact-checking using the wisdom of crowds. *Science Advances*, *7*(36), eabf4393.

Allen, J., Howland, B., Mobius, M., Rothschild, D., & Watts, D. J. (2020). Evaluating the fake news problem at the scale of the information ecosystem. *Science advances*, *6*(14), eaay3539.

Althaus, S. L., & Tewksbury, D. (2000). Patterns of internet and traditional news media use in a networked community. *Political communication*, *17*(1), 21–45.

Atoy Jr, M. B., Garcia, F. R. O., Cadungog, R. R., Cua, J. D. O., Mangunay, S. C., & De Guzman, A. B. (2020). Linking digital literacy and online information searching strategies of philippine university students: The moderating role of mindfulness. *Journal of Librarianship and Information Science*, *52*(4), 1015–1027.

Benkler, Y., Faris, R., & Roberts, H. (2018). *Network propaganda: Manipulation, disinformation, and radicalization in american politics*. Oxford University Press.

Boggioni, T. (2021). Capitol rioters blame conservative media misinformation for hoodwinking them into jan. 6: Report. *Salon*. Retrieved May 30, 2021, from https://www.salon.com/2021/05/30/capitol-rioters-blame-conservative-media-misinformation-for-hoodwinking-them-into-jan-6-report_partner/

Breakstone, J., Smith, M., Connors, P., Ortega, T., Kerr, D., & Wineburg, S. (2021). Lateral reading: College students learn to critically evaluate internet sources in an online course. *The Harvard Kennedy School Misinformation Review*.

Clayton, K., Blair, S., Busam, J. A., Forstner, S., Glance, J., Green, G., Kawata, A., Kovvuri, A., Martin, J., Morgan, E., et al. (2019). Real solutions for fake news? measuring the effectiveness of general warnings and fact-check tags in reducing belief in false stories on social media. *Political Behavior*, 1–23.

Constine, J. (2017). Facebook puts link to 10 tips for spotting 'false news' atop feed. https://techcrunch.com/2017/04/06/facebook-puts-link-to10-tips-for-spotting-false-news-atop-feed/

DiFonzo, N., & Bordia, P. (2007). Rumor, gossip and urban legends. *Diogenes*, *54*(1), 19–35.

Druckman, J. N. (2022). A framework for the study of persuasion. *Annual Review of Political Science*, *25*, 65–88.

Dutton, W. H., Reisdorf, B., Dubois, E., & Blank, G. (2017). Search and politics: The uses and impacts of search in britain, france, germany, italy, poland, spain, and the united states.

Eady, G., Bonneau, R., Tucker, J. A., & Nagler, J. (2020). *News Sharing on Social Media: Mapping the Ideology of News Media Content, Citizens, and Politicians*, SSRN. https://papers.ssrn.com/sol3/papers.cfm?abstract%7B%5C_%7Did=3721668

Edwards, L. (2021). Conspiracy theories, misinformation fueled riots at the capitol on jan. 6. *Fox17*. Retrieved February 8, 2021, from https://www.fox17online.com/homepage-showcase/conspiracy-theories-misinformation-fueled-people-riots-at-the-capitol-on-jan-6

Flanagin, A. J., & Metzger, M. J. (2000). Perceptions of internet information credibility. *Journalism & Mass Communication Quarterly*, *77*(3), 515–540.

Flanagin, A. J., & Metzger, M. J. (2007). The role of site features, user attributes, and information verification behaviors on the perceived credibility of web-based information. *New media & society*, *9*(2), 319–342.

Fogg, B. J., Marshall, J., Laraki, O., Osipovich, A., Varma, C., Fang, N., Paul, J., Rangnekar, A., Shon, J., Swani, P., et al. (2001). What makes web sites credible? a report on a large quantitative study. *Proceedings of the SIGCHI conference on Human factors in computing systems*, 61–68.

Gaines, B. J., & Kuklinski, J. H. (2011). Experimental estimation of heterogeneous treatment effects related to self-selection. *American Journal of Political Science*, *55*(3), 724–736.

Golebiewski, M., & boyd, D. (2019). Data voids: Where missing data can easily be exploited. *Data & Society*.

Gomila, R. (2020). Logistic or linear? estimating causal effects of experimental treatments on binary outcomes using regression analysis. *Journal of Experimental Psychology: General.*

Granka, L. A. (2010). The politics of search: A decade retrospective. *The Information Society*, *26*(5), 364–374.

Greenspan, R. (2021). The qanon conspiracy theory and a stew of misinformation fueled the insurrection at the capitol. *Insider*. Retrieved January 7, 2021, from https://www.insider.com/capitol-riots-qanon-protest-conspiracy-theory-washington-dc-protests-2021-1

Grinberg, N., Joseph, K., Friedland, L., Swire-Thompson, B., & Lazer, D. (2019). Fake news on twitter during the 2016 us presidential election. *Science*, *363*(6425), 374–378.

Guess, A., Lerner, M., Lyons, B., Montgomery, J. M., Nyhan, B., Reifler, J., & Sircar, N. (2020). A digital media literacy intervention increases discernment between mainstream and false news in the united states and india. *Proceedings of the National Academy of Sciences*, *117*(27), 15536–15545.

Guess, A., Lyons, B., Montgomery, J., Nyhan, B., & Reifler, J. (2018). Fake news, facebook ads, and misperceptions: Assessing information quality in the 2018 us midterm election campaign. *Democracy Fund report. www. dartmouth. edu/˜ nyhan/fake-news-2018. pdf.*

Hu, D., Jiang, S., E. Robertson, R., & Wilson, C. (2019). Auditing the partisanship of google search snippets. *The World Wide Web Conference*, 693–704.

Jürgens, P., & Stark, B. (2017). The power of default on reddit: A general model to measure the influence of information intermediaries. *Policy & Internet*, *9*(4), 395–419.

Kalsnes, B. (2018). *Deciding what's true: The rise of political fact-checking in american journalism.* Taylor & Francis.

Kaňuková, N. et al. (2019). Searching for alternative facts: Analyzing scriptural inference in conservative news practises. *Media Literacy and Academic Research*, *2*(1), 119–120.

Latzer, M., Hollnbuchner, K., Just, N., & Saurwein, F. (2016). The economics of algorithmic selection on the internet. *Handbook on the economics of the internet.* Edward Elgar Publishing.

Loomba, S., de Figueiredo, A., Piatek, S. J., de Graaf, K., & Larson, H. J. (2021). Measuring the impact of covid-19 vaccine misinformation on vaccination intent in the uk and usa. *Nature human behaviour*, *5*(3), 337–348.

Marwick, A., & Partin, W. (2020). Qanon shows that the age of alternative facts will not end with trump. *Columbia Journalism Review*.

McCarthy, B. (n.d.). Misinformation and the jan. 6 insurrection: When 'patriot warriors' were fed lies. *PolitiFact*. https://www.politifact.com/article/2021/jun/30/misinformation-and-jan-6-insurrection-when-patriot/

Montgomery, J. M., Nyhan, B., & Torres, M. (2018). How conditioning on posttreatment variables can ruin your experiment and what to do about it. *American Journal of Political Science*, *62*(3), 760–775.

Moravec, P., Minas, R., & Dennis, A. R. (2018). Fake news on social media: People believe what they want to believe when it makes no sense at all. *Kelley School of Business Research Paper*, (18-87).

Munger, K. (2020). All the news that's fit to click: The economics of clickbait media. *Political Communication*, *37*(3), 376–397.

Pennycook, G., McPhetres, J., Zhang, Y., Lu, J. G., & Rand, D. G. (2020). Fighting covid-19 misinformation on social media: Experimental evidence for a scalable accuracy-nudge intervention. *Psychological science*, *31*(7), 770–780.

Pennycook, G., & Rand, D. G. (2019). Lazy, not biased: Susceptibility to partisan fake news is better explained by lack of reasoning than by motivated reasoning [The Cognitive Science of Political Thought]. *Cognition*, *188*, 39–50.

Pennycook, G., & Rand, D. G. (2020). Who falls for fake news? the roles of bullshit receptivity, overclaiming, familiarity, and analytic thinking. *Journal of personality*, *88*(2), 185–200.

Persily, N., & Tucker, J. A. (2020). *Social media and democracy: The state of the field, prospects for reform*. Cambridge University Press.

Peterson, E., & Iyengar, S. (2021). Partisan gaps in political information and information-seeking behavior: Motivated reasoning or cheerleading? *American Journal of Political Science*, *65*(1), 133–147.

Robertson, R. E., Lazer, D., & Wilson, C. (2018). Auditing the personalization and composition of politically-related search engine results pages. *Proceedings of the 2018 World Wide Web Conference*, 955–965.

Starbird, K., Dailey, D., Mohamed, O., Lee, G., & Spiro, E. S. (2018). Engage early, correct more: How journalists participate in false rumors online during crisis events. *Proceedings of the 2018 CHI conference on human factors in computing systems*, 1–12.

Vosoughi, S., Roy, D., & Aral, S. (2018). The spread of true and false news online. *Science*, *359*(6380), 1146–1151.