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

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

[a]Center for Social Media and Politics, New York University
[b]Wilf Family Department of Politics, New York University
[c]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 increases the probability of believing misinformation, in some cases by up to 26%. To shed light on this relationship, we combine survey and digital trace data, collected using a custom browser extension, to investigate the cause. We find that the search effect is concentrated among individuals for whom search engines return low-quality information. Our results demonstrate that those who search online to evaluate misinformation risk falling into data voids, or informational spaces where there is plenty of corroborating evidence from low-quality 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 replace a general focus on online search with more targeted techniques that teach individuals how to use proper search terms and identify quality news sources.

[*]**Acknowledgement:** This material is based upon work supported by the National Science Foundation under Grant 2029610.

[*]**Disclaimer:** Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

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 misinformation (SOEM) 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 (Dutton et al., 2017), 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, such as Google, with the goal of reducing belief in misinformation. Although search engines play a key role in how people evaluate information online,

[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

we know little about how SOEM impacts 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, Lerner, et al., 2020). In this manuscript, we present for the first time, to our knowledge, the results from experimental studies identifying how SOEM 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 this may be the case: 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 plethora of unreliable information available to be returned by search engines (Golebiewski and boyd, 2019), particularly in the period directly after publication of false content. Searches in these cases may expose users to other low-quality information, but thus far no empirical evidence has evaluated whether or not exposure to low-quality information returned by search engines affects belief in misinformation. We therefore also measure the effect of SOEM on belief in misinformation when individuals are exposed to unreliable information returned by search engines.

To this end, we run five separate experiments that measure the effect of SOEM on belief in misinformation. 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 SOEM on belief in popular misinformation by utilizing different types of experiments (within-subjects and between subjects) and in a variety of contexts.

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 search engine results on belief in misinformation. By collecting search results using a custom web browser plug-in, we can identify how the quality of these search results may affect users' belief in the misinformation being evaluated. Given that

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

consumers of false news online often encounter these stories shortly after publication,[7] we collected respondent evaluations and digital trace data within 72 hours of publication. A study run months or years after publication would test the impact of a different set of search engine results, and it would be impossible to replicate the original results present in the period of most likely exposure. In addition, it is important we test the effect SOEM in real time, because misinformation often arises in an uncertain information environment present at the time of publication where individual's feel a psychological need for understanding (DiFonzo and Bordia, 2007). To truly measure the effect of SOEM we must run this study during the period in which the misinformation is circulating. To this end, these studies test the effect of SOEM within the information environment misinformation was originally generated and most likely to be consumed.

For all five of the studies, we utilized a pre-registered pipeline that sourced the most popular articles from a variety of "streams" of potential articles, and then distributed them to respondents and professional fact-checkers.[8] To remove the possibility of researcher selection bias when selecting the articles to be sent to respondents for assessment, we developed a transparent, replicable article selection algorithm (See the Methods section for a full explanation of this process.).

Taken together, the five studies provide consistent evidence that SOEM increases belief in misinformation and that the quality of results returned by search engines are a key driver of belief. In our fifth study, 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. Finally, we also find suggestive evidence that the effect of low-quality search results on believing misinformation is not concentrated among individuals with low levels of digital literacy or those congruent with the ideological perspective of the item of misinformation. Taken together, our results emphasize the effect of SOEM on belief in misinformation, and provide empirical evidence suggesting that unreliable information returned by search engines increases belief in misinformation.

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

[8] 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 main-stream 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 all of 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 SOEM 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.[9] 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 professional fact-checks were likely not available. To this end, we sent out the articles to be evaluated 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." 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.[10] In this paper 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.[11]

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 level to predict belief in misinformation (i.e. rating a false or misleading article as true).[12] 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

[9] 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.

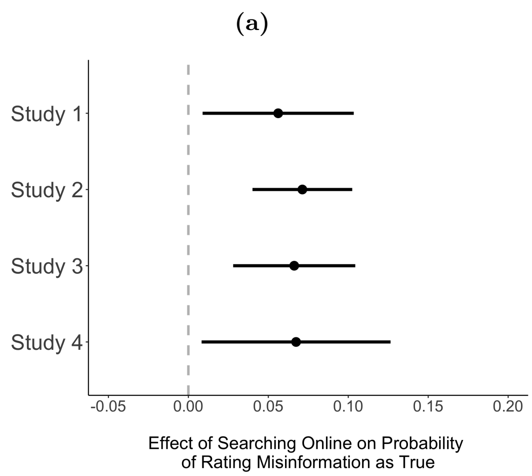
[10] We labeled articles as "could not determine if there was no unique mode or the modal fact-checker evaluation was "could not determine."

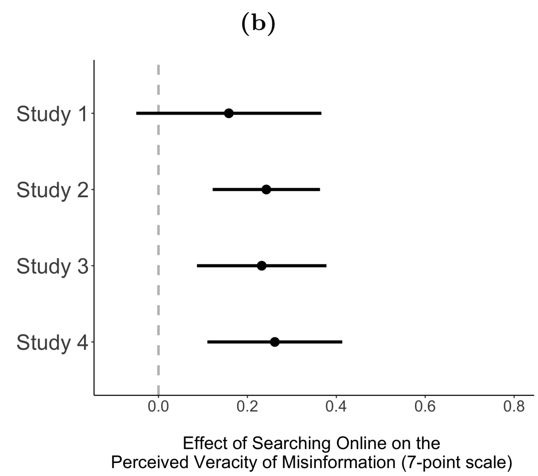
[11] Details about these articles can be found in Section A1 of the Supplementary Materials.

[12] 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).

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 respectively.[13] Figure 1a shows that being encouraged to search online increased the probability a respondent rated a false or misleading article as true by 0.055 (F=7.815, P=0.0382 ; for the full regression table see Section B of the Supplementary Materials). As the proportion of people in the control group that believed the false article to be true was 0.30, this represents close to a 18% increase in the probability of respondents rating misinformation as true when encouraged to SOEM. Figure 1b shows a 0.15 increase in perceived veracity using a 7-point ordinal scale (F=10.52, P=0.154).

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 SOEM during Studies 1, 2, 3, and 4. Panel a presents the effect of SOEM on rating misinformation as true. Panel b presents the effect of SOEM 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-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

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

over 33 days who were presented with one false/misleading popular online article within 48 hours of publication.[14] 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 (F=6.892, P<0.0001), a 22% increase in the probability of believing misinformation and an increase in 0.22 (F=7.098, P=0.0004) on a 7-point ordinal scale.[15] 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.

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 SOEM. This high quality information could eliminate, or, even more optimistically, change the 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 are more policy-relevant.

To measure the effect of SOEM 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

[14]Details about these articles can be found in Section A2 of the Supplementary Materials.
[15]For the full regression table see Section B of the Supplementary Materials.

study, we recruited 2,022 respondents American individuals 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 SOEM 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 0.063 (F=8.158, P=0.0034), which means 18% more respondents rated the same false/misleading story as true after they were asked to re-evaluate the article post-treatment.[16] A similar effect was identified using an ordinal scale (0.22 increase on a 7-point scale ; F=8.756, P=0.0015). 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 SOEM on belief in misinformation.

The first three studies measure the effect of SOEM on popular pieces of misinformation, which are often written about niche topics not covered 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 SOEM 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 SOEM 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 respondents through Qualtrics.[17] Respondents were presented with at least one false/misleading online Covid-related article within 72 hours of publication.[18] 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

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

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

[18] 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.

rates a false/misleading article as true by 0.067 (F=4.567, P=0.0451), or an increase in belief in misinformation of 20% and an increase by 0.26 on a 7-point ordinal scale (F=4.629, P=0.0054).[19]

Taken together, Studies 1–4 present consistent evidence across a variety of experimental designs, time periods, and topics that SOEM 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 SOEM increases belief in misinformation.

Can Exposure to Unreliable Information Explain Why SOEM 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).[20] Second, unreliable news sources often re-use stories from each other, polluting search engine results with other similar non-credible stories. 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 corroborating 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.

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

[20] Golebiewski and boyd (2019) state that these 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 investigate the prevalence and effect of exposure to unreliable information while SOEM, 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 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 collected the URLs they visited 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 articles from mainstream and low-quality sources within 72 hours of publication.[21] Over the course of this study, fourteen different false/misleading articles were evaluated by individuals in the control (952 evaluations from 624 unique respondents) and treatment group (653 evaluations from 451 unique respondents).[22] 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 in the control group.[23] 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. 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.[24]

Figure 2a presents the proportion of search queries about true and false/misleading articles that return unreliable news sources in 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

[21] 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.

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

[23] When we analyze the effect of the quality of searching engine results, we only include those in the control and treatment group who kept their web extension on during the survey to limit possible selection bias effects.

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

(August, 2021).[25] A histogram of NewsGuard scores for the majority of online news domains can be found in Section C of the Supplementary Materials.[26] 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 12% of search queries about true articles return at least one unreliable news link among the top ten results, whereas 32% of search queries about false/misleading articles return at least one unreliable news link among the top ten results.

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.[27] 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. In this study, the effect of SOEM is larger than in the previous studies, likely because the treatment is stronger in this study relative to the others.[28] In this final study, searching online increased the probability a respondent rated a false or misleading article as true by 0.105 (F=9.187, P=.0119), which is almost double the effect observed in previous studies. This represents a greater than 26% increase in the probability of respondents rating a false or misleading story as true when encouraged to search online. Searching online also increased the average score by 0.15 (F=12.149, P=0.0467) on a 4-point ordinal scale and 0.16 (F=11.430, P=0.2155) on a 7-point ordinal scale.

Using digital trace data collected through the custom browser plug-in, we were able to measure the effect of SOEM 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

[25] 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 journalistic criteria. The criteria assess basic practices of credibility and transparency based on a site's performance on nine criteria, assigning a score from 0 to 100 indicating its credibility. Anything with a score below 60 is deemed as unreliable and anything above 60 is 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/.

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

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

[28] 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.

were exposed to Google search engine results that returned (1) at least one unreliable news site in the top ten results returned,[29] and (2) only very reliable news sites in the top ten results returned.[30] Half of all evaluations in the treatment group fit in either of these two subsets.[31] Among these two subsets Figure 2c shows that 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. Indeed, in Figure 2d we 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 and report similar results. Results from Figure 2c show 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 SOEM increases belief in misinformation. In addition, we actually find that respondents who search online about misinformation and are exposed to the highest quality of information are slightly less likely to believe misinformation than those in the control group. To be clear, we are not inferring a causal relationship between the quality of information returned in Google search engine and belief in misinformation from this analysis. By conditioning on a post-treatment variable we remove the causal leverage gained by the random assignment of the treatment because we are comparing dissimilar groups (Montgomery et al., 2018) and therefore cannot make a causal claim. Rather than a causal argument, we can only confirm that this evidence appears consistent with the low-quality search results mechanism, but there are other plausible theories to explain these results. For example, it is possible that Google search engines are more likely to return low-quality news to individuals who are already more predisposed to believe misinformation. Either Google Search engine's algorithm or the search terms that individuals enter could explain why those who are exposed to more unreliable news are more likely to believe a false or misleading article.

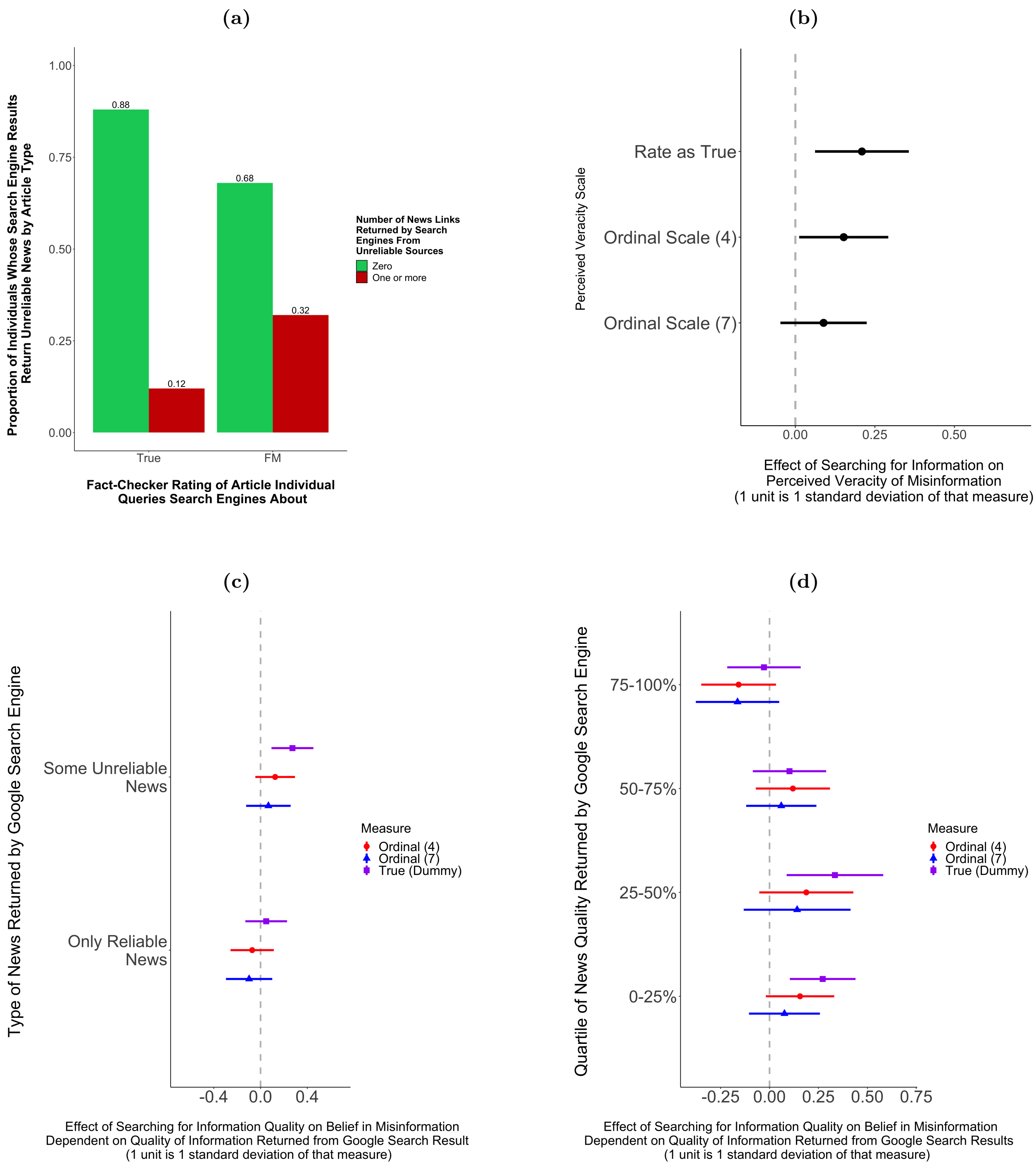
[29] Newsguard considers sites with a rating of 60 or below (out of 100) as unreliable.

[30] News sites are considered very reliable if they are given a score of 90 or higher by NewsGuard.

[31] 31.5% of the 508 evaluations fit in the "some unreliable news" group and 18.7% of the 508 evaluations fit in the very reliable news sites group. Although subsetting the data in this way ignores 50% of the data, we 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.

But if our explanation is indeed correct, it remains unclear why individuals could be persuaded by low-quality news sources. In the survey, respondents are asked to find *"credible"* sources to help them evaluate the veracity of the news articles, mirroring many media literacy interventions. Why then do individuals allow low-quality sources to influence their evaluation? In the next section, we consider whether evidence from our work is consistent with two plausible interpretations for why individual's evaluations could be influenced by low-quality information: motivated reasoning and digital literacy.

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, but subset the treatment group by the quality of news respondents are exposed to when they search online about misinformation.



Why does Unreliable Information Affect Belief in Misinformation?

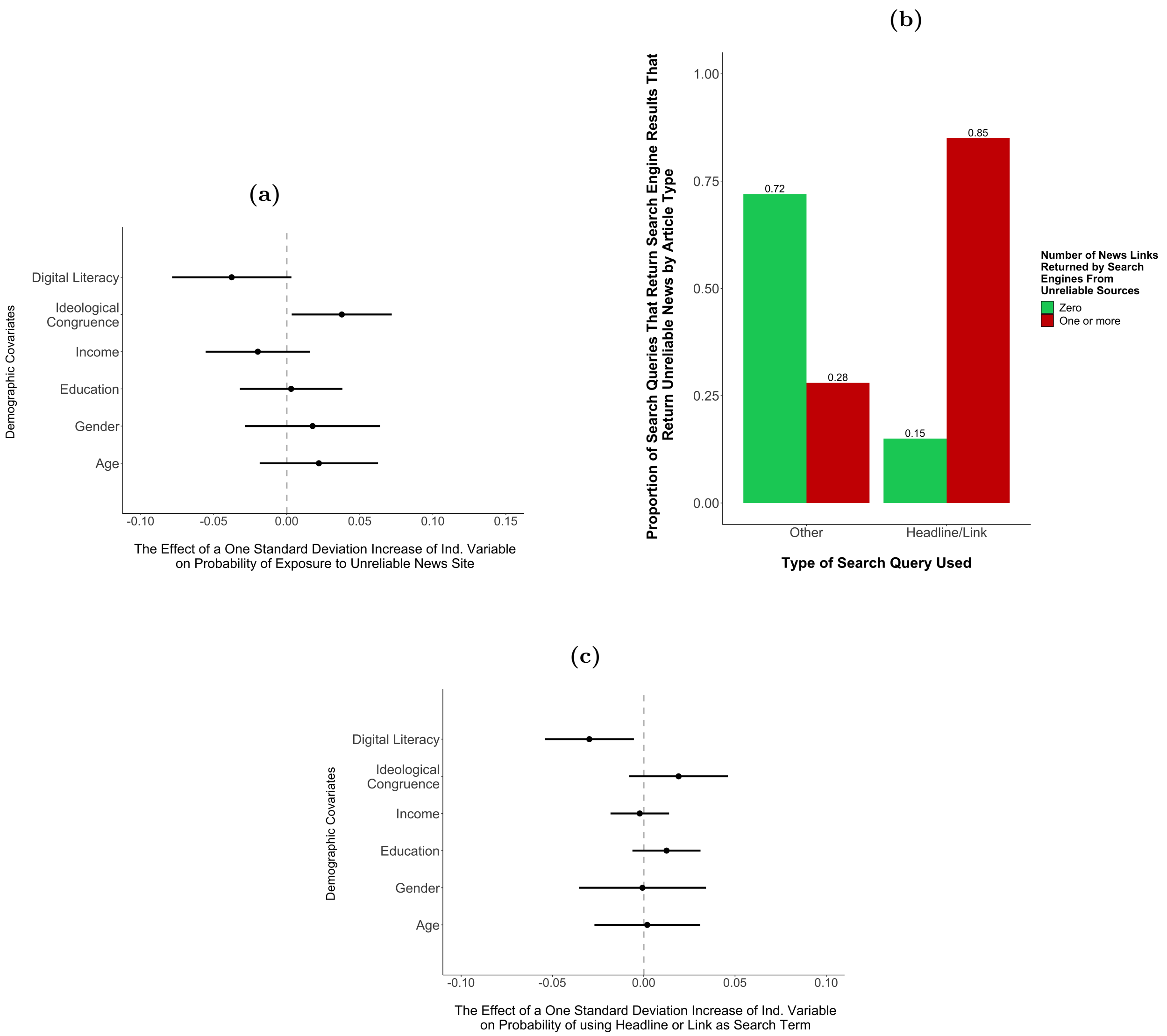
In this section, we assess the viability of two possible explanations for why exposure to low-quality news in search engine results may increase belief in misinformation: (1) motivated reasoning and (2) low levels of digital literacy. In the motivated reasoning account, partisans seek out information from ideological congruent sources, even if they are unreliable, and may adopt inaccurate beliefs that portray their preferred political party in a favorable light (Peterson and Iyengar, 2021). If the respondent is congruent with the ideological perspective of the misinformation, they may be more likely to both be exposed to seek out and believe low-quality results in a search engine that support the initial false article, given that it is consistent with their own views (Allcott and Gentzkow, 2017; Kahan, 2017; Moravec et al., 2018; Van Bavel and Pereira, 2018). To this end, we investigate whether exposure to low-quality search results and the effect of being exposed 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 both more likely to fall into these data voids and less able to discern between low-quality and high-quality information returned in search engine results. Previous research has suggested that lower levels of digital literacy among older individuals may explain why they are more likely to share and view misinformation on social media (Guess et al., 2021; Guess et al., 2019). News returned in search engines are particularly difficult to evaluate because source cues are largely obscured in the results. Online news consumers often rely on the professionalism of the design of a website to determine the news quality of online sources (Flanagin and Metzger, 2007; Fogg et al., 2001), but this is not available if individuals rely solely on the page of search engine results. Source cues may also come through reputation (Althaus and Tewksbury, 2000; Flanagin and Metzger, 2000), but low-quality news sources likely have no general reputation given that consumption of low-quality news is concentrated among a small proportion of online news consumers (Guess, Nyhan, et al., 2020). To this end, we determine whether exposure to low-quality search results and the effect of being exposed to low quality search results is concentrated among those with low levels of digital literacy.

To assess the empirical support for these two potential explanations, we begin by exploring which basic demographic 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. Figure 3a presents the effect of a one standard deviation increase of each demographic variable on the probability of being exposed to at least one unreliable news story in the search engine results when SOEM. Evidence from these results suggest that lower levels of digital literacy and ideological congruence with the ideological perspective of the misinformation correlates with exposure to unreliable news in search results, although we have slightly lower confidence in the effect of digital literacy. A standard deviation decrease in digital literacy increases the probability of being exposed to unreliable news by a Google search engine by 0.38 (F=3.563, P=0.0841). A standard deviation increase in ideological congruence also increases the probability of being exposed to unreliable news by a Google search engine by 0.38 (F=3.563, P=0.0327).

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. Figure 3b shows that those that 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. 85% 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 28% 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. In addition, 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. Figure 3c presents the results of this model and shows that those with lower levels of digital literacy are much more likely to use the headline or the unique URL of the false article as their search query when SOEM. A standard deviation decrease in digital literacy increases the probability of using the headline or the unique URL of the false article as their search query by 0.03 (F=2.411, P=0.0269).

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.

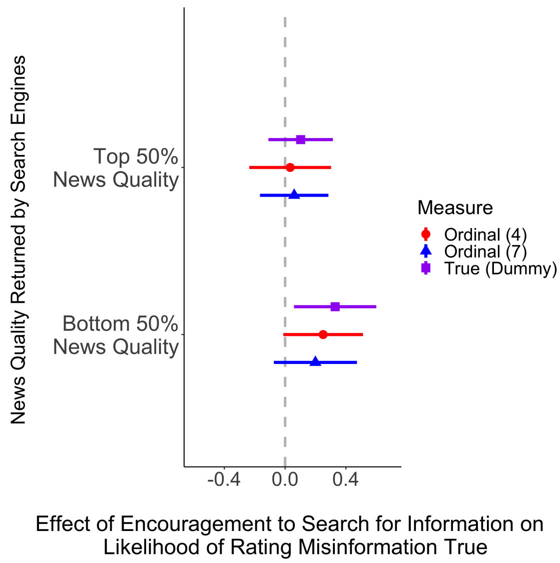


But once exposed to unreliable information in search engine results, who is more likely to believe the false article they evaluated? To identify which groups may be more susceptible to unreliable news in search results, we again turn to the data from Study 5 to measure the marginal effect of SOEM among those with high and low levels of digital literacy, as well as those who are ideologically congruent and incongruent to the misinformation they are evaluating. Among those who received the treatment, we further subset to those who were exposed to Google search engine results that returned: (1) news quality in the top half of Google search engine results (above the median average NewsGuard rating of news returned by Google Search engine results about an item of misinformation) or (2) news quality in the bottom half of Google search engine results (below the median average NewsGuard rating of news returned by Google Search engine results about an item of misinformation). Figure 4 shows that, for those exposed to the bottom half of news quality, the probability an individual believes misinformation after searching online is higher than the control group among each subset of respondents. Taken together, lower quality information returned in search engine results appears to increase belief in misinformation equally among those with high and low levels of digital literacy, as well as those congruent and incongruent to the ideological perspective of the item of misinformation.[32] Combined with our previous findings, this suggests that those with lower levels of digital literacy and ideological congruence to the misinformation are more likely to be exposed to lower quality news when they SOEM, but are not more likely to be influenced by low-quality news.

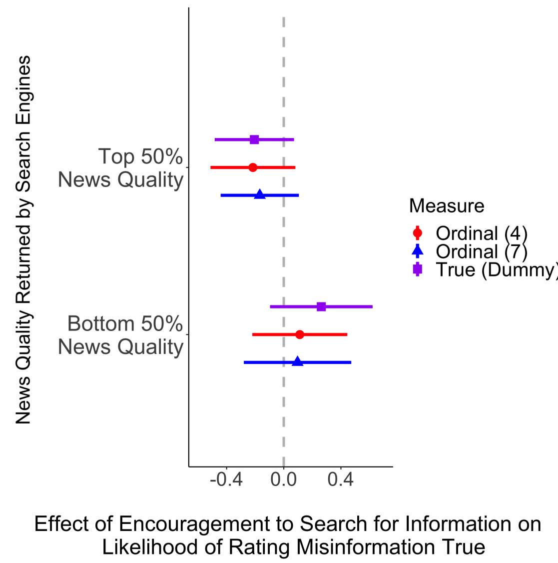
[32] To be clear, as we stated earlier, by subsetting on a post-treatment variable, these relationships are not causal.

Figure 4: Who is Most Susceptible to Unreliable Information when Searching for More Information? (Study 5). Panels a through d present 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. Marginal effect sizes are subset by the quality of news returned in their search engine results. Panels a through d present the effect of being encouraged to search online among those in the bottom half of digital literacy (a), those in the top half of digital literacy (c), those ideologically congruent with the ideological perspective of the item of misinformation they are evaluating (b), and those ideologically incongruent with the ideological perspective of the item of misinformation they are evaluating (d).

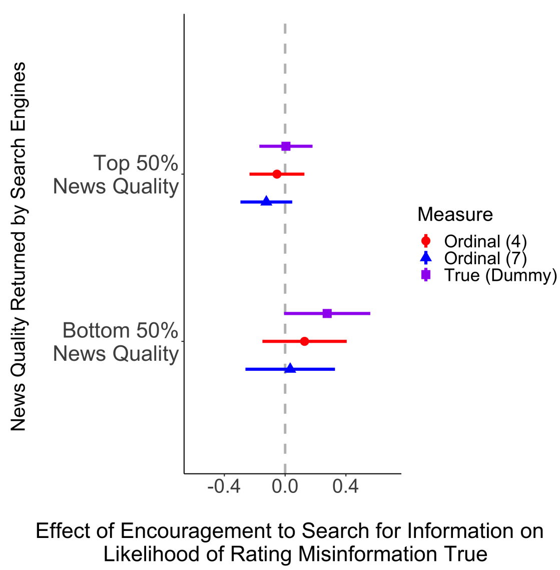
(a) Respondents with Low Levels of Digital Literacy



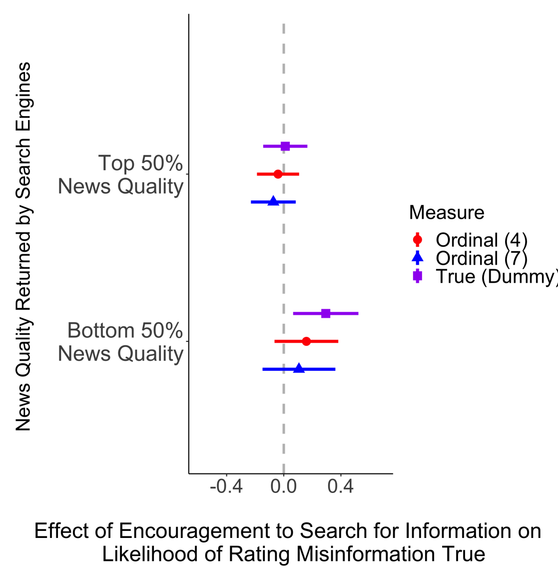
(b) Respondents who are Ideologically Congruent to the Ideological Perspective of the Misinformation



(c) Respondents with High Levels of Digital Literacy



(d) Respondents who are Ideologically Incongruent to the Ideological Perspective of the Misinformation



Discussion

While significant 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 misinformation (SOEM) *increases* belief in popular misinformation by measurable amounts. This result is consistent and robust across five separate studies in 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) and using respondents recruited by Qualtrics and respondents recruited on Mechanical Turk. In our fifth study, which applies the strongest treatment, encouraging individuals to SOEM increased belief in misinformation by 26%. Other studies with slightly weaker SOEM encouragements also report similarly large increases in belief in misinformation.

To better understand the finding 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 confirm 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 relative to when individuals search about true news. In addition, this exposure matters: those who are exposed to low-quality information are more likely to believe misinformation relative to those who are not. We then adjudicated between two possible explanations for why exposure to more low quality information might make people more likely to believe false news stories: motivated reasoning and digital literacy. Although we do find that 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 SOEM, we do not find that the effect of the news quality on belief in misinformation varies across the two groups.

The QAnon movement recommends that people "do the research" themselves (Marwick and Partin, 2020), which at first glance 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. Ironically, media literacy guides also place an emphasis on SOEM. 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, our findings show that exposure to low-quality sources in search results is correlated with higher belief in false or misleading articles, and that low-quality sources are more likely to be returned when using the headline or URL of the stimulus. Building off of this, media literacy programs should replace a general focus on online search with more targeted techniques that teach individuals how to use proper search terms and identify quality news sources.

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).[33] 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, 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 is

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

whether one's ideological perspective is congruent to the piece of misinformation, not ideology in itself that affects belief in misinformation, 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 that searching online increases belief in misinformation than the results we present in the main text of this paper.

Article Selection Process

To distribute a representative sample of popular news articles directly after publication to respondents, we created a transparent, replicable, and pre-registered article selection process that sourced popular false/misleading and true articles from across the ideological spectrum to be evaluated by respondents within 24-48 hours of their publication.[34] 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, 2, 3, and 4) or Amazon's Mechanical Turk (Study 5).[35] Collecting and distributing the most popular false articles directly after publication is a key innovation that enabled us to measure the effect of SOEM 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.[36] To classify these websites as liberal or conservative, we used scores of media partisanship from Eady et al.

[34] In Study 4 (where we only sent articles about Covid-19 to respondents), we delayed sending the articles to respondents for 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, for example, an incorrect Covid-19 treatment.

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

[36] 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.[37] 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 of these low-quality sources into three streams: liberal leaning sources, conservative leaning sources, and those with no clear partisan orientation.[38]

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.[39] Articles chosen by this algorithm therefore represent the most popular credible and low quality news from across the ideological spectrum.[40] 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 articles that had been selected on that day by our article selection protocol as well as a litany of demographic questions.[41] Respondents evaluated each article using a variety of criteria, the

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

[38] 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.

[39] 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/.

[40] 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.

[41] 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).[42] 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" using 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).[43] 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.[44]

Determining Veracity of Articles Distributed

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 engage with this content online.

[42]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

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

[44]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.[45] 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.[46] This level of agreement 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). 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.

Study 1

In Study 1, we tested whether SOEM 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 after searching online. We predicted in a pre-registered report[47] that false/misleading 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).

[45] 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.

[46] 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.

[47] 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). You can find the articles used during this study 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."[48] 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.: The central claim you are evaluating is factually accurate. 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.

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

Instructions To Find Evidence To Evaluate Central Claim

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.[49]

We then presented respondents with the following four questions:

(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?[50]

(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.

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

[50] 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.

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

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 (Female)	0.52	0.49	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 18th, 2019 and February 6th, 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 is a conceivably 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 it's 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.[51] 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 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.[52]

Summary Statistics

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

Table 2: Summary Statistic of participants in Study 2

Demographic	Mean	Standard Deviation
Education	2.36	1.24
Age	44.79	17.41
Gender (Female)	0.47	0.5
Income	1.04	1
Ideology	0.01	1.74

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

Study 3

Study 3 replicated Study 2 using the same materials and procedure, but was run between March 16th, 2020 and April 28th, 2020, three to five months after the publication of each these articles. This study set out to test if this search effect held even months after the publication of this 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 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)	0.51	0.5
Income	0.95	0.95
Ideology	-0.04	1.76

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

Study 4

Study 4 extended Study 2 by asking individuals to evaluate and re-evaluate popular misinformation strictly about Covid-19 after searching online. This study was run between May 28th, 2020 to June 22nd, 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	2.36	1.24
Age	44.79	17.41
Gender (Female)	0.47	0.5
Income	1.04	1
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). Similar to Study 1, we measured the effect of SOEM on belief in misinformation in a randomized controlled trial that ran on twelve separate days from July 13th, 2021 to November 9th, 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.

Over twelve days during Study 5, a group of respondents were encouraged to SOEM 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.

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 only 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	3.54	3.53	0.01
Age	37.59	39.31	-1.72
Gender (Female)	0.45	0.48	-0.03
Income	1.76	1.79	-0.03
Ideology	-0.54	-0.57	0.03

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

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

Demographic	Average (Complier)	Average (Non-Complier)	Difference
Education	3.43	3.67	-0.24
Age	36.56	39.11	-2.55
Gender (Female)	0.41	0.52	-0.11*
Income	1.73	1.75	-0.02
Ideology	-0.61	0.23	-0.84***
Digital Literacy	55.14	49.03	6.11***

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

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 we were able to collect this digital trace data for 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 very much 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 very much difference 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	3.43	3.49	-0.06
Age	36.56	39.13	-2.57***
Gender (Female)	0.41	0.47	-0.06*
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.

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

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/

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.

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.

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

Guess, A., Aslett, K., Tucker, J. A., Bonneau, R., & Nagler, J. (2021). Cracking open the news feed: Exploring what us facebook users see and share with large-scale platform data. *Journal of Quantitative Description: Digital Media*, *1*.

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., Nagler, J., & Tucker, J. A. (2019). Less than you think: Prevalence and predictors of fake news dissemination on facebook. *Science advances*, *5*(1), eaau4586.

Guess, A., Nyhan, B., & Reifler, J. (2020). Exposure to untrustworthy websites in the 2016 us election. *Nature Human Behaviour*, *4*(5), 472–480.

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.

Kahan, D. (2017). Misconceptions, misinformation, and the logic of identity-protective cognition (cultural cognition project working paper series no. 164; yale law school, public law research paper no. 605; yale law & economics research paper no. 575).

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., Jiang, S., Joseph, K., Friedland, L., Lazer, D., & Wilson, C. (2018). Auditing partisan audience bias within google search. *Proceedings of the ACM on Human-Computer Interaction*, *2*(CSCW), 1–22.

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.

Van Bavel, J. J., & Pereira, A. (2018). The partisan brain: An identity-based model of political belief. *Trends in cognitive sciences*, *22*(3), 213–224.

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