Effects of Misinformation on Election Beliefs: Disentangling Motivated Reasoning from Selective Exposure

Ross Dahlke & Jeffrey T. Hancock

July 26, 2024

Abstract

The proliferation of misinformation, especially during critical periods such as election seasons, challenges democratic processes worldwide. Combining a two-wave panel study with web-browsing behavior (N = 21M) of 1,194 American adults around the 2020 U.S. Presidential Election, we find that those exposed to at least one misinformation website are 17.3% more likely to believe that the election was fraudulent in a post-election survey. However, one challenge in assessing the effects of misinformation is disentangling the behavior of individuals selectively exposing themselves to misinformation congenial to an existing belief versus prior political identities heterogeneously leading to differing effects on beliefs. To disentangle selective exposure from motivated reasoning, we apply a causal machine learning method that controls for the propensity to be exposed to a misinformation website. Using this approach, we quantify the association between exposure to misinformation websites and false election beliefs. Using this method, we find exposure to misinformation is associated with the likelihood of false election beliefs by 4.2%. This effect, however, is asymmetric and consistent with a motivated reasoning account: for conservatives, whose candidate lost the election, the association is 12.6%, while for liberals, the association is negligible at -0.2%. Further, we identify a dosage effect, where each additional exposure to misinformation websites increases the association between misinformation website exposure and false election beliefs among conservatives by .035% but only .010% for liberals. These findings contribute to our understanding of misinformation's real-world effects, demonstrating a significant impact on election validity beliefs that vary by political orientation and exposure frequency. Our results underscore the importance of addressing misinformation not as a uniform influence but as a factor whose effects are contingent upon individual predispositions and exposure volume.

Introduction

Among global leaders, misinformation[information that is false, misleading, or unsubstantiated, 1] was recently listed as society's biggest problem[2]. This sentiment is bolstered by academic research[3] that has found tens of millions of American adults are exposed to misinformation during election seasons[4–7]. Although misinformation constitutes a relatively small portion of people's information diets[8–10], it is also highly concentrated, with a small number of people accounting for the majority of exposures or clicks[11,12].

While these descriptive findings are important to understanding the reach and distribution of misinformation, they typically do not shed light on the real-world effects of being exposed to misinformation. That is, what are the societal consequences of misinformation? Past experimental work examining the effect of misinformation on vaccine hesitancy generally finds that exposure has a small effect on vaccine intentions and behaviors[e.g., 13,14,15]. Other work on the effect of misinformation on climate change skepticism finds a limited effect[e.g., 16,17]. In the political sphere, other experimental research suggests that individuals are susceptible to forming false memories around political events when shown fabricated news stories[e.g., 18] or images[e.g., 19] compared to participants who were not shown fabrications. Similarly, participants who were experimentally exposed to misinformation about the frequency of fraud in American elections are more likely to support postponing the election[e.g., 20] compared to participants not shown this misinformation.

Last, exposure to a single piece of misinformation may increase voting intention but has limited effects on other political beliefs and behaviors[21].

To overcome the limitations of experimental work on estimating the effects of misinformation on beliefs[22], researchers have used observational methods that generally find significant, albeit limited, correlations between misinformation exposure and the outcome of interest. For example, past work has found a positive correlation between exposure to misinformation websites and false beliefs, but not intentions to participate in politics[21]. There is also a correlation between engaging with election-related misinformation on Twitter and voter turnout[23]. Those who shared misinformation on Twitter promoting election fraud misinformation were less likely to vote. However, other work has not found a strong relationship between visiting untrustworthy websites and belief in political misperceptions[24].

While these observational studies mitigate some external validity concerns, they are often limited to establishing correlations between exposures and outcomes. Such correlations, while informative, raise concerns about issues like reverse causality[22,25] and how these concerns affect the interpretation of a given study's findings. Said another way, current observational studies have difficulty distinguishing whether misinformation exposure affects people's beliefs or if people seek out misinformation that aligns with their prior beliefs.

Conceptually, correlations between exposure and outcome conflate two distinct mechanisms that may underlie the relationship between misinformation exposure and beliefs: selective exposure and motivated reasoning. Selective exposure refers to a tendency for people who already hold certain beliefs to seek out consistent information[26–29]. For example, conservative individuals are more likely to expose themselves to conservative misinformation and liberal individuals to liberal misinformation [[5]; moore2022]. Motivated reasoning refers to how people are motivated to arrive at or justify specific conclusions to new information based on desired beliefs[30,31], ultimately accepting information consistent with desired beliefs and rejecting contradictory information[30,31]. For example, political affiliations change the ways that people interpret political information[32–36], and therefore impact politically consequential beliefs[37–40], including conspiracy theory and false beliefs[41–43].

Examining only the correlation between exposure and outcome may mask these underlying processes. For example, do people who already believe that an election is fraudulent seek out and selectively expose themselves to information that supports this belief? Or, do prior political affiliations shape the interpretation of information via motivated reasoning to lead people to believe misinformation that the election is fraudulent? In other words, if there is evidence of misinformation's effect, even after controlling for selective exposure, then motivated reasoning would suggest that the results should be asymmetrical by political identity. That is, misinformation exposure should influence beliefs that the election was fraudulent for supporters of the losing candidate to a larger degree than supporters of the winning candidate.

We seek to disentangle selective exposure and motivated reasoning. We do so by examining real-world exposure to misinformation websites in the months before and after the 2020 U.S. Presidential election and estimating the effect of these exposures on beliefs regarding the validity of the election. Using an application of a double machine learning method developed for causal inference in econometrics[44], we advance on past observational work by controlling for selective exposure and find that misinformation exposure is associated with an increase in false election beliefs by 4.2% (95% CI = 0.3, 8.0). In contrast, a simple t-test that does not control for selective exposure suggests that those exposed are 17.3% more likely to believe the election was fraudulent, the difference between these two estimates suggests that selective exposure plays a role in the association between exposure and beliefs.

Furthermore, motivated reasoning would suggest the interpretation of misinformation through the lens of prior political affiliations[45] leading supporters of the losing candidate to have a stronger association between misinformation and false election beliefs compared to supporters of the winning candidate. Consistent with motivated reasoning, the association between misinformation and false election beliefs we observe is asymmetric. For the 2020 election, in which the conservative candidate lost, conservatives had a conditional average treatment effect (CATE) of believing the election was fraudulent of 12.6% (95% CI [1.7, 23.5]), while, for liberals, the effect was -0.2% (95% CI [-1.9, 1.6]). We also find a dosage effect for each misinformation exposure of .034%, indicating that the belief that the election was fraudulent saw small but significant increases

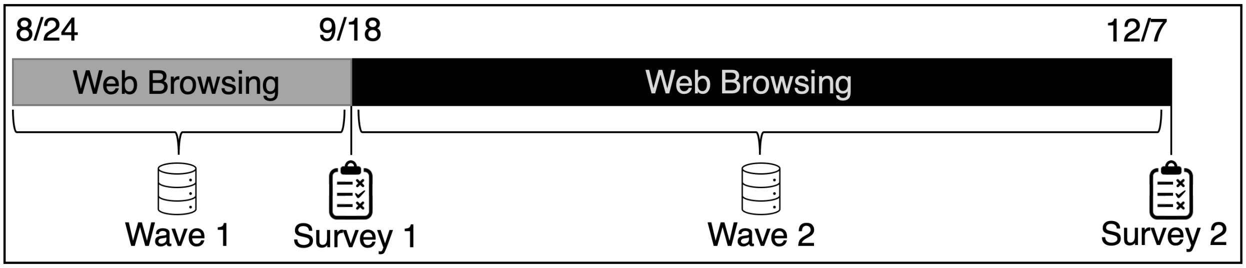

Figure 1: Timeline of data collection. The first wave of web-browsing data was collected from August 24, 2020, to September 18, 2020. We administered a survey on September 18, 2020, to collect demographic information and political support. The second wave of web-browsing data was collected from September 19, 2020, to December 7, 2020. Then, we conducted a second survey on December 7, 2020, and asked participants about their beliefs on whether the 2020 U.S. Presidential Election was stolen

with each new exposure. Again consistent with motivated reasoning, this dosage effect was asymmetric: the average treatment effect for conservatives was .035% (95% CI [-.017, .054]) and .010% (95% CI [-.020, 0.41]) for liberals.

The Causal Forest method comes with statistical assumptions, namely the unconfoundedness assumption, that no unobserved variable confounds exposure to misinformation websites and false election beliefs. Thus, we first interpret these findings as associative. However, a causal sensitivity analysis suggests that the results are unlikely to be "explained away" by a hypothetical unobserved confounder. Any unobserved confounding variable would need to confound the results more than prior misinformation exposure, gender, race, political knowledge, political interest, and age to "explain away" the significant relationship we find between misinformation exposure and false election beliefs. The results of this causal sensitivity analysis provide evidence of a causal interpretation of our findings.

Misinformation Exposure & False Belief Measurement

We collected data from 1,194 participants recruited by the survey firm YouGov. These participants completed Survey 1 on September 18, 2020, seven weeks before the U.S. Presidential Election, and Survey 2 on December 7, 2020, four weeks after the Presidential Election. We also gathered two waves of web-browsing data from the participants using YouGov's Pulse web-tracking software. The first wave of browsing data was collected from August 24, 2020, to September 18, 2020, and the second wave of web-browsing data was collected from September 19, 2020, to December 7, 2020. Figure 1 summarizes the data collection process.

All participants consented to the surveys and installed the web-tracking software, and YouGov compensated them for their participation. YouGov weighted these individuals to match a nationally representative population, and we used these weights in the regressions. The data and code supporting this study's findings are available in OSF with the identifier 10.31219/osf.io/325tn[46]. We complied with all relevant ethical regulations. The Stanford University Institutional Review Board (IRB) approved the study protocol.

To measure our main dependent variable, we asked participants, "In your view, who won the presidential election held in November?" on December 7, 2020, in Survey 2. Notably, December 7, 2020, was a month after the election and one month before the January 6 protests, being one of the first academic studies to measure this belief. The answer to this question is our dependent variable of belief that the election was fraudulent. In our survey, 19.7% (95% CI [17.4, 22.0]) of people said they believed Donald Trump was the rightful winner, including 47.0% (95% CI [42.3, 51.8]) of Trump supporters. Importantly, research has found that this belief is genuinely held and is not "expressive responding" to demonstrate partisan membership[47,48].

The main independent variables of interest are misinformation website exposure and the number of misinformation website exposures in Wave 2 of the web-browsing data. To identify which websites our participants visited that were misinformation websites, we used a list of 1,796 misinformation domains from[6]. We use a variety of variables as the observable control variables in our analyses, including being a conservative (Trump supporter), education level, gender, race, political knowledge, political interest, and age. We also control for digital behaviors of exposure to misinformation websites in Wave 1 and the total number of websites visited. Then, exposure to a misinformation website during Wave 2 of the web-browsing data is our independent variable of interest.

Misinformation Effect Estimation Method

We used a Causal Forest to estimate the average treatment effect (Wager, 2018). Causal Forest is a doubly robust nonparametric machine learning method. It flexibly adjusts for observed differences to estimate the average difference between people exposed to misinformation websites and those who were not. This method is preferential to a simple OLS regression because it non-parametrically considers the propensity to be treated (exposed to misinformation) based on the known variables of each individual. These propensities are then considered when calculating the average treatment effect. Additionally, this method allows us to examine heterogeneity in the results easily. For comparable results under a simpler parametric regression framework, see Supplemental Materials A.

Like other double machine learning methods, Causal Forests (Wager, 2018) use two main steps to estimate treatment effects under a predicted outcomes framework. In the first machine learning step, we train a machine learning model to predict whether individual i is exposed to at least one misinformation website. For binary exposure, the methodology uses observed variables

$$X$$

for each individual and W, whether that individual received the treatment (i.e., exposed to misinformation), to estimate the propensity of receiving the treatment, $\hat{W}$. In our case

$$X_i = \begin{bmatrix} Conservative_i \\ PoliticalKnowledge_i \\ PoliticalInterest_i \\ Female_i \\ EduHSorLess_i \\ EduSomeCollege_i \\ EduCollegeGrad_i \\ EduPostGrad_i \\ RaceBlack_i \\ RaceHispanic_i \\ RaceWhite_i \\ RaceOther_i \\ AgeUnder30_i \\ Age30to44_i \\ Age45to65_i \\ Age65plus_i \\ MisinfoExposureWave1_i \\ WebVisitsWave1_i \end{bmatrix}$$

Findings

We integrate survey data from 1,194 people and passively-collected web-browsing data from the participants, consisting of nearly 21 million website visits. These data were collected over two periods (see Fig. 1). The first baseline period of browsing data was collected from August 24, 2020, to September 18, 2020, with a survey to collect demographic information administered September 18, 2020. We also collected a second period of browsing data from the same participants from September 19, 2020, to December 7, 2020. On December

7, 2020, four weeks after the U.S. Presidential Election, we administered another survey and collected the participants' beliefs about the validity of the election results. We identify misinformation website exposures in the browsing data by matching the domains the participants visited with a list of known misinformation sites[6]. We also conducted a supplemental analysis where we only examined misinformation website visits that refer specifically to the election, finding similar results (see Supplemental Information E).

and $W_i = ExposedMisinfo_i$, with W_i being "0" if not exposed to at least one misinformation website and "1" if exposed. This first machine learning step is flexible regarding the method used to estimate $\hat{W}$. For example, one could use a simple logistic regression or a more complex neural network to predict exposure. In this manuscript, we follow Wager & Athey's (2018) "Causal Forest" methodology and use random forests with 2,000 trees with a target minimum node size of 5, 50% of the data being used to build each tree, "honest" fitting (see Wager & Athey, 2018 for more details on these parameters).

In the second machine learning step, the observed variables X are considered along with $\hat{W}$. In order to focus on the population that we can measure (with confidence) and desire to measure an effect for (the general population that may or may not be exposed to misinformation websites), we use the method suggested by Li (2018) to estimate the treatment effect, $\tau(x)$. More formally, this all comes together as

(1)

$$\tau(x) = E[e(X)(1 - e(X))(Y^{(1)} - Y^{(0)})/E[e(X)(1 - e(X))$$

, where $e(x) = P[W_i = 1|X_i = x]$. Said in plain words, under the predicted outcomes framework we use the trained machine learning model to predict the outcome of interest (i.e., belief that the election was fraudulent) for each individual under two scenarios: a scenario in which the individual was exposed to misinformation in the second wave ($Y^{(1)}$) and a scenario in which they were not exposed ($Y^{(0)}$). The individual treatment effect (ITE) is difference between these two predictions. We then use each individuals' likelihood to be exposed to misinformation (i.e., their propensity to selectively expose themselves to misinformation, $\hat{W}$) as a weight to calculate the average treatment effect (ATE). To calculate the dosage effect, we repeat this process but with W being the number of exposures to misinformation (i.e., not a binary variable).

Misinformation Effect Estimation Results

While our main estimate of interest is the effect of misinformation exposure on the belief in the validity of the results of the 2020 U.S. Presidential Election, we describe the results of both steps of the machine learning pipeline (i.e., a model predicting exposure and a model predicting the belief that the election was fraudulent). First, we examine wave 2 misinformation exposure. In our data, 39.6% (95% CI [36.8, 42.4]) of our participants were exposed to at least one misinformation website in wave 2. While past studies have examined the predictors of exposure, for example, finding that older adults and conservatives are more likely to be exposed to misinformation[e.g., 5,6], we approach this step as a prediction problem. The random forests used to predict exposure are well calibrated in a heteroskedasticity-consistent test of calibration ($p < .001$; AUC = 0.754, see Supplemental Materials B), showing that the model accurately predicts wave 2 misinformation exposure on held-out data. In examining variable importance (see Supplemental Materials C), wave 1 misinformation exposure is unsurprisingly by far the most "important" variable in predicting wave 2 exposure. The next most important variables are political knowledge, being a conservative, and political interest. This predicted propensity to be exposed to misinformation in wave 2 is then considered as a weight, shown formally in Equation (1) and visually in Supplemental Materials C. Conceptually, we argue that the incorporation of this first machine learning model into the second allows us to control for selective exposure (i.e., the predisposition to expose oneself to misinformation websites).

Next, we turn to the second machine learning model and use the resulting predictions with the predicted outcomes framework to answer RQ1: Does misinformation affect the belief that the election was fraudulent after controlling for selective exposure? Exposure to misinformation indeed increases the belief that the election was fraudulent by 4.2% (95% CI [0.3, 8.0]) on average (see Figure 2).

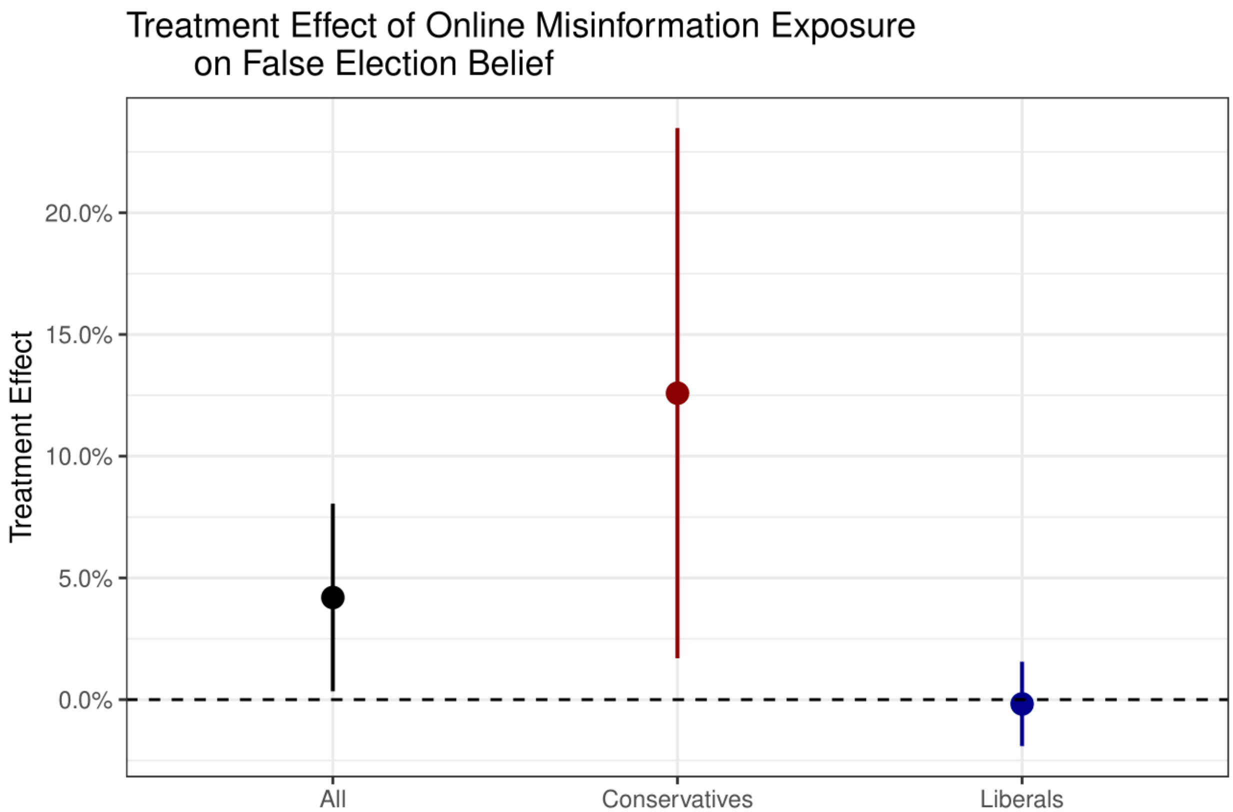

Figure 2: Plot of Average Treatment Effect (ATE) and Conditional Average Treatment Effects (CATE) and 95% confidence interval of misinformation website exposure on the belief that Donald Trump won the 2020 U.S. Presidential Election. The x-axis represents different groups of people: all participants in our sample, conservatives, and liberals. The y-axis represents the (C)ATE of misinformation exposure on the belief that the election was stolen for the given group.

However, our motivated reasoning prediction would suggest that these results should be asymmetric by political identity, with conservatives being affected more than liberals. Consistent with H1, we find a conditional average treatment of 12.6% (95% CI [1.7, 23.5]) for conservatives and –0.2% (95% CI [-1.9, 1.6]) for liberals (see Figure 2; for Individual Treatment Effects [ITEs] see Supplemental Materials D), meaning that conservatives were much more susceptible to the effects of misinformation on beliefs about the election's validity in the context of the 2020 U.S. Presidential Election. The random forests used to predict this outcome are calibrated in a heteroskedasticity-consistent test of calibration ($p = .02$; AUC = 0.752, see Supplemental Materials B).

Finally, turning to RQ2, whether the dosage of misinformation matters, we repeat the process above, but with dosage as the independent variable of interest (i.e., the number of wave 2 misinformation exposures), we find an average estimated dosage effect of .034% (95% CI [.018, .049]), suggesting that for each additional exposure to a misinformation website, the likelihood of falsely believing the election was stolen increased by .03%. Consistent with motivated reasoning, we also observe an asymmetry in the dosage effect. The dosage effect for conservatives was .035% (95% CI [.017, .054]) and for liberals, .010% (95% CI [-.020, .041]). We initially interpret all of these results as associative. However, in Supplemental Materials E, we cannot reasonably "explain away" the results through robustness checks on the statistical assumptions of the method.

Discussion

We examine the effect of actual exposure to misinformation websites on the belief that the 2020 U.S. Presidential Election was fraudulent. After controlling for selective exposure via double machine learning, we find that exposure to online misinformation significantly affects this belief. The 17.3% topline difference between those exposed to misinformation and those not decreases to a 4.2% difference when controlling for selective exposure. This result suggests that 75.7% of this topline difference can be explained by selective exposure, leaving 24.3% as the remaining difference–a difference that cannot be reasonably "explained away" and thus may be reasonably interpreted as a causal effect. As predicted by motivated reasoning, the effect is entirely asymmetric. We find a larger effect for conservatives, whose candidate lost, than for liberals, whose candidate won. We also find a dosage effect that was similarly asymmetric, with additional misinformation exposures increasing the belief that the election was fraudulent for conservatives more than for liberals.

These effects align with prior work suggesting that misinformation can influence a variety of beliefs. However, in addressing the novel question of the effect of misinformation on false election beliefs, we examine actual misinformation exposure and overcome a shortcoming of past observational work that conflates selective exposure and the actual effect of misinformation[22]. The heterogeneity we find in the effect, that the losing party's supporters are more affected by misinformation in holding the false belief that the election was fraudulent, is also consistent with political communication research that finds that partisans respond more positively to congenial information via motivated reasoning. This evidence of motivated reasoning in misinformation effects contrasts concerns that misinformation is a hypodermic needle, automatically changing beliefs upon exposure[49]. Instead, misinformation's effects are likely felt in very specific contexts by only a select number of individuals about salient and congenial topics. For example, in the present study, where the conservative candidate lost the presidential election, conservatives were more susceptible to misinformation and its effects on false beliefs about the validity of the election. In other electoral outcomes, the effect of misinformation should be observed among other populations. For example, in the 2016 U.S. Presidential Election when the liberal candidate lost, the conspiracy that Russia directly tampered with voting machine counts to help the conservative candidate[50–52] was embraced by supporters of the liberal candidate, but not by conservatives[53].

This heterogeneity is particularly important in the context of the dosage effect. Past work on misinformation effects has drawn on literature on the illusory truth effect[e.g., 54,55–58]. This theory states that repeated exposure to information is more likely to cause a change as opposed to a single exposure[59–61]. Indeed, we find that the dosage is a key component in the story of misinformation effects. However, the illusory truth effect suggests homogeneity in the effect, with repeated exposures accumulating in an effect without heterogeneity. Instead, our results demonstrate that repeated misinformation exposure is important and deserves more study. However, the heterogeneity in dosage effects also suggests that the illusory truth effect may only activate in the context of motivated reasoning under certain types of information.

While our study overcomes some limitations of past work, it carries its own assumptions. First, just like other web-browsing studies, we analyze website visits at the domain level[5,6]. This domain level means that not every URL from a misinformation website may necessarily be misinformation. However, this limitation is shared across other studies using similar data. Furthermore, although the causal forest methodology relaxes some statistical assumptions from other double machine learning methods, particularly normality, other assumptions carry over, including adequate fit of machine learning models, omitted variable bias, and no unobserved confounders. However, we conducted various robustness tests to that suggest our results are not reasonably "explained away" through these tests (see Supplemental Materials E). Future work can find cleaner causal estimates by examining exogenous shocks in observational (e.g., changes in content moderation policies) or field experiments that expose people or prevent misinformation in a natural setting.

References

1. Nyhan, B. & Reifler, J. When corrections fail: The persistence of political misperceptions. *Political Behavior* **32**, 303–330 (2010).
2. WEF. *Global risks report 2024.* (2024).
3. Weeks, B. E. & Gil de Zúñiga, H. What's next? Six observations for the future of political misinformation research. *American Behavioral Scientist* **65**, 277–289 (2021).
4. Guess, A., Lyons, B., Montgomery, J., Nyhan, B. & Reifler, J. Fake news, facebook ads, and misperceptions: Assessing information quality in the 2018 US midterm election campaign democracy fund report. (2018).
5. Guess, A. M., Nyhan, B. & Reifler, J. Exposure to untrustworthy websites in the 2016 US election. *Nature human behaviour* **4**, 472–480 (2020).
6. Moore, R., Dahlke, R. & Hancock, J. Exposure to untrustworthy websites in the 2020 US election. *Nature human behaviour* (2023).
7. Zhou, A., Yang, T. & González-Bailón, S. The puzzle of misinformation: Exposure to unreliable content in the united states is higher among the better informed. *new media & society* 14614448231196863 (2023).
8. Allcott, H. & Gentzkow, M. Social media and fake news in the 2016 election. *Journal of economic perspectives* **31**, 211–236 (2017).
9. Allen, J., Howland, B., Mobius, M., Rothschild, D. & Watts, D. J. Evaluating the fake news problem at the scale of the information ecosystem. *Science advances* **6**, eaay3539 (2020).
10. Altay, S., Nielsen, R. K. & Fletcher, R. Quantifying the 'infodemic': People turned to trustworthy news outlets during the 2020 coronavirus pandemic. *Journal of Quantitative Description: Digital Media* **2**, (2022).
11. Grinberg, N., Joseph, K., Friedland, L., Swire-Thompson, B. & Lazer, D. Fake news on twitter during the 2016 US presidential election. *Science* **363**, 374–378 (2019).
12. Guess, A., Nagler, J. & Tucker, J. Less than you think: Prevalence and predictors of fake news dissemination on facebook. *Science advances* **5**, eaau4586 (2019).
13. Allen, J., Watts, D. J. & Rand, D. G. Quantifying the impact of misinformation and vaccine-skeptical content on facebook. *Science* **384**, eadk3451 (2024).
14. Featherstone, J. D. & Zhang, J. Feeling angry: The effects of vaccine misinformation and refutational messages on negative emotions and vaccination attitude. *Journal of Health Communication* **25**, 692–702 (2020).
15. Saint Laurent, C. de, Murphy, G., Hegarty, K. & Greene, C. M. Measuring the effects of misinformation exposure and beliefs on behavioural intentions: A COVID-19 vaccination study. *Cognitive Research: Principles and Implications* **7**, 87 (2022).
16. Drummond, C., Siegrist, M. & Árvai, J. Limited effects of exposure to fake news about climate change. *Environmental Research Communications* **2**, 081003 (2020).
17. Zhou, Y. & Shen, L. Confirmation bias and the persistence of misinformation on climate change. *Communication Research* **49**, 500–523 (2022).
18. Murphy, G., Loftus, E. F., Grady, R. H., Levine, L. J. & Greene, C. M. False memories for fake news during ireland's abortion referendum. *Psychological science* **30**, 1449–1459 (2019).
19. Frenda, S. J., Knowles, E. D., Saletan, W. & Loftus, E. F. False memories of fabricated political events. *Journal of Experimental Social Psychology* **49**, 280–286 (2013).
20. Craig, S. C. & Gainous, J. To vote or not to vote? Fake news, voter fraud, and support for postponing the 2020 US presidential election. *Politics & Policy* **52**, 33–50 (2024).
21. Guess, A. M. *et al.* 'Fake news' may have limited effects beyond increasing beliefs in false claims. *HKS Misinformation Review* (2020).
22. Guess, A. M. & Lyons, B. A. Misinformation, disinformation, and online propaganda. *Social media and democracy: The state of the field, prospects for reform* **10**, (2020).

23. Green, J., Hobbs, W., McCabe, S. & Lazer, D. Online engagement with 2020 election misinformation and turnout in the 2021 georgia runoff election. *Proceedings of the National Academy of Sciences* **119**, e2115900119 (2022).
24. Weeks, B. E., Menchen-Trevino, E., Calabrese, C., Casas, A. & Wojcieszak, M. Partisan media, untrustworthy news sites, and political misperceptions. *New Media & Society* **25**, 2644–2662 (2023).
25. Adams, Z., Osman, M., Bechlivanidis, C. & Meder, B. (Why) is misinformation a problem? *Perspectives on Psychological Science* **18**, 1436–1463 (2023).
26. Freedman, J. L. & Sears, D. O. Selective exposure. in *Advances in experimental social psychology* vol. 2 57–97 (Elsevier, 1965).
27. Sears, D. O. & Freedman, J. L. Selective exposure to information: A critical review. *Public Opinion Quarterly* **31**, 194–213 (1967).
28. Stroud, N. J. Polarization and partisan selective exposure. *Journal of communication* **60**, 556–576 (2010).
29. Zillmann, D. & Bryant, J. *Selective exposure to communication.* (Routledge, 2013).
30. Epley, N. & Gilovich, T. The mechanics of motivated reasoning. *Journal of Economic perspectives* **30**, 133–40 (2016).
31. Kunda, Z. The case for motivated reasoning. *Psychological bulletin* **108**, 480 (1990).
32. Bisgaard, M. How getting the facts right can fuel partisan-motivated reasoning. *American Journal of Political Science* **63**, 824–839 (2019).
33. Guay, B. & Johnston, C. D. Ideological asymmetries and the determinants of politically motivated reasoning. *American Journal of Political Science* **66**, 285–301 (2022).
34. Liang, H. & Zhang, X. Partisan bias of perceived incivility and its political consequences: Evidence from survey experiments in hong kong. *Journal of Communication* **71**, 357–379 (2021).
35. Slothuus, R. & De Vreese, C. H. Political parties, motivated reasoning, and issue framing effects. *The Journal of Politics* **72**, 630–645 (2010).
36. Weeks, B. E. Emotions, partisanship, and misperceptions: How anger and anxiety moderate the effect of partisan bias on susceptibility to political misinformation. *Journal of communication* **65**, 699–719 (2015).
37. Han, J. & Federico, C. M. The polarizing effect of news framing: Comparing the mediating roles of motivated reasoning, self-stereotyping, and intergroup animus. *Journal of Communication* **68**, 685–711 (2018).
38. Levendusky, M. S. Why do partisan media polarize viewers? *American journal of political science* **57**, 611–623 (2013).
39. Little, A. T., Schnakenberg, K. E. & Turner, I. R. Motivated reasoning and democratic accountability. *American Political Science Review* **116**, 751–767 (2022).
40. Vegetti, F. & Mancosu, M. The impact of political sophistication and motivated reasoning on misinformation. *Political Communication* **37**, 678–695 (2020).
41. Enders, A. M. & Smallpage, S. M. Informational cues, partisan-motivated reasoning, and the manipulation of conspiracy beliefs. *Political Communication* **36**, 83–102 (2019).
42. Miller, J. M., Saunders, K. L. & Farhart, C. E. Conspiracy endorsement as motivated reasoning: The moderating roles of political knowledge and trust. *American Journal of Political Science* **60**, 824–844 (2016).
43. Pillai, R. M., Kim, E. & Fazio, L. K. All the president's lies: Repeated false claims and public opinion. *Public opinion quarterly* **87**, 764–802 (2023).
44. Wager, S. & Athey, S. Estimation and inference of heterogeneous treatment effects using random forests. *Journal of the American Statistical Association* **113**, 1228–1242 (2018).
45. Bolsen, T., Druckman, J. N. & Cook, F. L. The influence of partisan motivated reasoning on public opinion. *Political Behavior* **36**, 235–262 (2014).
46. Dahlke, R. & Hancock, J. The effect of online misinformation exposure on false election beliefs. (2024) doi:10.31219/osf.io/325tn.
47. Fahey, J. J. & Alarian, H. M. *The big lie: Expressive responding and conspiratorial beliefs in the united states.* (2022).

48. Graham, M. H. & Yair, O. Expressive responding and trump's big lie. in *Papre presented at the annual meeting of the midwest political science association* (2022).
49. Bello-Pardo, E. *A digital hypodermic needle? Essays on the impact of misinformation, framing, and images on american public opinion in the internet age.* (American University, 2022).
50. Albertson, B. & Guiler, K. Conspiracy theories, election rigging, and support for democratic norms. *Research & Politics* **7**, 2053168020959859 (2020).
51. Levy, M. Winning cures everything? Beliefs about voter fraud, voter confidence, and the 2016 election. *Electoral Studies* **74**, 102156 (2021).
52. Sinclair, B., Smith, S. S. & Tucker, P. D. 'It's largely a rigged system': Voter confidence and the winner effect in 2016. *Political Research Quarterly* **71**, 854–868 (2018).
53. Frankovic, K. Belief in conspiracies largely depends on political identity. *YouGov* (2016).
54. Pennycook, G., Cannon, T. D. & Rand, D. G. Prior exposure increases perceived accuracy of fake news. *Journal of experimental psychology: general* **147**, 1865 (2018).
55. Newman, E. J., Jalbert, M. C., Schwarz, N. & Ly, D. P. Truthiness, the illusory truth effect, and the role of need for cognition. *Consciousness and Cognition* **78**, 102866 (2020).
56. Jalbert, M., Newman, E. & Schwarz, N. Only half of what i'll tell you is true: Expecting to encounter falsehoods reduces illusory truth. *Journal of Applied Research in Memory and Cognition* **9**, 602–613 (2020).
57. Udry, J. & Barber, S. J. The illusory truth effect: A review of how repetition increases belief in misinformation. *Current Opinion in Psychology* 101736 (2023).
58. Vellani, V., Zheng, S., Ercelik, D. & Sharot, T. The illusory truth effect leads to the spread of misinformation. *Cognition* **236**, 105421 (2023).
59. Ernst, N., Kühne, R. & Wirth, W. Effects of message repetition and negativity on credibility judgments and political attitudes. *International Journal of Communication* **11**, 21 (2017).
60. Fazio, L. K., Rand, D. G. & Pennycook, G. Repetition increases perceived truth equally for plausible and implausible statements. *Psychonomic bulletin & review* **26**, 1705–1710 (2019).
61. Hassan, A. & Barber, S. J. The effects of repetition frequency on the illusory truth effect. *Cognitive research: principles and implications* **6**, 38 (2021).