

# Measuring exposure to misinformation from political elites on Twitter

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**Misinformation can come directly from public figures and organizations (referred to here as “elites”). Here, we develop a tool for measuring Twitter users’ exposure to misinformation from elites based on the public figures and organizations they choose to follow. Using a database of professional fact-checks by PolitiFact, we calculate falsity scores for 816 elites based on the veracity of their statements. We then assign users an elite misinformation-exposure score based on the falsity scores of the elites they follow on Twitter. Users’ misinformation-exposure scores are negatively correlated with the quality of news they share themselves, and positively correlated with estimated conservative ideology. Additionally, we analyze the co-follower, co-share, and co-retweet networks of 5,000 Twitter users and find an ideological asymmetry: estimated ideological extremity is associated with more misinformation exposure for users estimated to be conservative but not for users estimated to be liberal. Finally, we create an open-source R library and an Application Programming Interface (API) making our elite misinformation-exposure estimation tool openly available to the community.**

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## Introduction

There has been growing public concern about misinformation on social media. Accordingly, a great deal of effort has been invested by practitioners and researchers into investigating the spread of online misinformation<sup>1,2</sup>. Prior work has largely focused on belief in, and sharing of, articles (often headlines) from reliable versus unreliable news domains. While this kind of misinformation was a particular focus of interest in the wake of the 2016 election cycle (e.g., far-fetched headlines from little-known publishers going viral), a different form of misinformation has begun to gain attention in recent years: coordinated misinformation campaigns orchestrated by public figures and organizations (i.e., referred to here as “elites”), such as the claims of widespread fraud in the 2020 U.S. Presidential Election made by Republican politicians<sup>3</sup>. Given the large body of evidence documenting the impact of political elites on voter attitudes and behaviors<sup>4-7</sup>, exploring exposure to elite-based misinformation (rather than just news domains) is important.

Furthermore, in focusing on what people believe and share, prior work has largely overlooked what (mis)information people are exposed to (a notable exception is ref<sup>8</sup>). Although exposure and sharing are obviously related (insomuch as you can only share content that you are exposed to), they are fundamentally different constructs. Most people share only a tiny fraction of the content they are exposed to<sup>8</sup>, and therefore examining the content someone shares provides a very limited picture of a person’s information environment. The choice of whom to follow (and thus what information to expose oneself to) is particularly important in light of evidence that simply being exposed to content, even if it is highly implausible, makes it subsequently seem truer<sup>9</sup>.

Here, we introduce an approach for studying misinformation on social media that specifically focuses on exposure to misinformation from elites (defined as public figures and organizations). In particular, we estimate Twitter users’ exposure to misinformation from elites by examining the extent to which they follow the accounts of elites who make false or inaccurate claims (based on PolitiFact ratings) to a greater or lesser degree. (We adapt an approach used in prior work for estimating social media users’ partisanship by examining the ideological leanings of the political elites they follow<sup>10</sup>, and apply that approach to misinformation.) The measure we introduce allows researchers to study users’ choices about what level of (mis)information to expose themselves to and provides a tool for scholars of elite cues and messaging to examine exposure to elite misinformation online (e.g., to examine how this exposure correlates with other measures of interest). Our measure also allows researchers who study sharing to take a step towards controlling for exposure when estimating effects on sharing and provides an outcome measure for Twitter field experiments (e.g., that try to motivate users to improve the information environment they are exposed to).

Our approach also helps to address a methodological challenge facing social media studies of misinformation. These kinds of studies typically involve examining the content users post on social media<sup>8,11,12</sup>, linking survey responses to social media data<sup>13,14</sup> or open web data<sup>15</sup>, or conducting field experiments on social media and measuring the impact of interventions on subsequent sharing<sup>16,17</sup> (for methodological reviews, see refs<sup>18-20</sup>). A key challenge for such studies is determining how to rate the quality of the content the users share or consume. The approach used in most prior studies is to assemble a list of domains with ratings: either a blacklist of domains classified as misinformation domains by journalists or fact-checkers, or continuous domain-level quality ratings generated by professional fact-checkers or crowd workers (e.g., ref<sup>21</sup>). These domain lists are then used to generate quality scores for each user (e.g., number of links to misinformation sites shared, average quality of links shared, etc.).

Although this domain-level approach has yielded many insightful results, there are important limitations. Nearly all prior work measures behavior that occurs after exposure – sharing<sup>8,14,16,17</sup> or clicking out to visit websites<sup>15,22</sup>. However, which content you are exposed to – and thus even have the chance to share or click on – is determined by the users you follow. Therefore, the choice of which accounts to follow has a profound impact on the information environment users experience online, but this choice has received much less attention from researchers in the study of misinformation. Additionally, there is a great deal of turnover among fake news sites (in part to evade social media platforms' efforts to block particularly egregious publishers). Thus, domain lists used in these approaches – which are incomplete to begin with – go stale fairly quickly, and there is no clear way to update the lists (e.g., no widely agreed-upon criteria for inclusion). And finally, by definition, the domain-based approach only captures posts with links – yet only a small minority of all posts contain links<sup>17</sup>, and thus a substantial amount of potentially misleading content is missed.

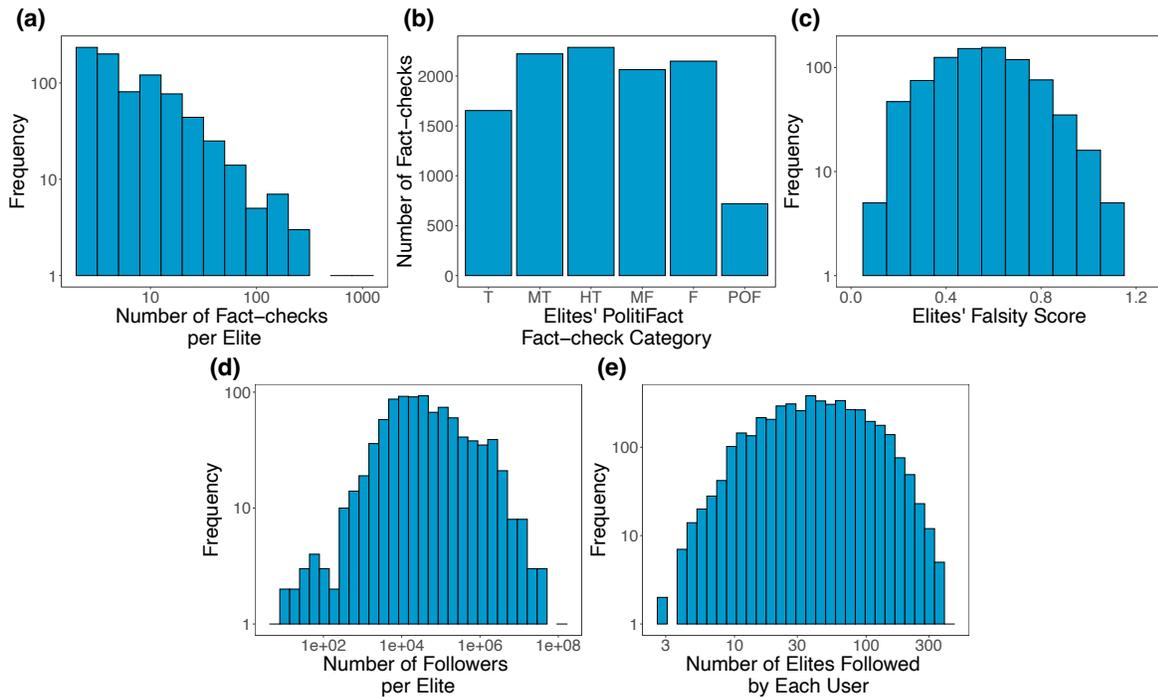
The approach we introduce here addresses these limitations. We leverage a large public database of professional fact-checks by PolitiFact to generate falsity scores (a number between 0 and 1 representing the veracity of statements made by an elite) for a range of elites (i.e., public figures and organizations). We then give each user a misinformation-exposure score by averaging the falsity scores associated with Twitter accounts of all the elites who the user choose to follow. Our approach measures the exposure of users to the content generated by the accounts they follow on Twitter, rather than relying on user behaviors. We use the accounts that a user follows as a proxy for what they would see in their feed. Additionally, our measure is based on a readily available public dataset of elites that is easily updated using fact-checking websites. Finally, our approach does not rely on identifying posts that include URLs. To make our measure broadly available to the research community, we also created an open-source R library and an API that calculates Twitter users' misinformation-exposure scores.

We then validate our approach by showing that the resulting misinformation-exposure scores correlate with the quality of information users share online. We also identify communities of accounts and domains that are preferentially followed and shared by users with high misinformation exposure and observe an ideological asymmetry such that estimated political extremity is more associated with misinformation exposure for users estimated to be conservatives compared to liberals.

## Results

### *Descriptives*

We begin with descriptives of the fact-checking data we collected from PolitiFact. Figure 1a shows the distribution of the number of fact-checks per elite. Restricting to accounts with at least three fact-checks (and who are therefore included in our study), Figure 1b shows the number of fact-checks per each category of rating, and Figure 1c shows the distribution of falsity scores associated with elites' Twitter accounts. Figure 1d shows the distribution of the elites' number of followers and Figure 1e shows the number of elites followed by each user in our sample.



*Figure 1. Descriptives of the fact-checking dataset that forms the basis of our elite misinformation exposure measure. (a) Distribution of number of fact-checks per elite provided by PolitiFact. (b) Number of fact-checks per each PolitiFact category (T: True, MT: Mostly True, HT: Half True, MF: Mostly False, F: False, POF: Pants on Fire). (c) Distribution of falsity scores associated with elites' Twitter accounts. (d) Distribution of number of followers of elites. (e) Distribution of number of elites followed by each user. Source data are provided as a Source Data file.*

### ***Misinformation exposure and users' characteristics***

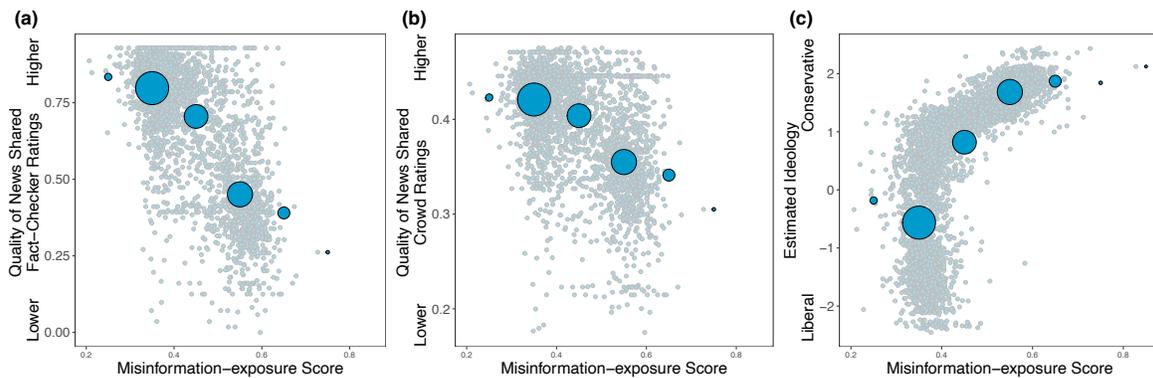
Next, we look at the relationship between users' misinformation-exposure scores (as measured by averaging the falsity scores of the elite Twitter accounts they followed) and their characteristics, estimated from their digital fingerprints on Twitter. Consistent with our expectation that following more misinformation-spreading accounts (and thus being exposed to more misinformation) should result in sharing more misinformation oneself, users' misinformation-exposure scores are negatively correlated with the quality of content they shared. We measured news quality using domain-level trustworthiness ratings, generated in two different ways. First, we used the average rating of eight professional fact-checkers. Second, we used ratings collected from a sample of 970 Americans quota-matched to the national distribution on age, gender, ethnicity, and geographic region; the average rating of respondents who preferred the Democratic party were averaged with the ratings of the respondents who preferred the Republican party to create politically balanced layperson ratings. Users' misinformation-exposure score was negatively associated with the quality of information shared using both the professional fact-checker ratings (Figure 2a;  $b=-0.728$ , 95% CI=[-0.753,-0.704], SE=0.013,  $t(3072)=-58.184$ ,  $p<0.001$ ) and the politically balanced layperson ratings (Figure 2b;  $b=-0.540$ , 95% CI=[-0.570,-0.510], SE=0.015,  $t(3072)=-35.299$ ,  $p<0.001$ ).

Aligned with prior work finding that people who identify as conservative consume<sup>15</sup>, believe<sup>23</sup>, and share more misinformation<sup>8,14,24</sup>, we also found a positive correlation between users' misinformation-exposure scores and the extent to which they are estimated to be conservative ideologically (Figure 2c;  $b=0.747$ , 95% CI=[0.727,0.767] SE=0.010,  $t(4332)=73.855$ ,  $p<0.001$ ), such that users estimated to be more conservative are more likely to follow the Twitter accounts of elites with higher fact-checking falsity scores. Critically, the relationship between misinformation-exposure score and quality of content shared is robust controlling for estimated ideology ( $b=-0.712$ , 95% CI=[-0.751,-0.673], SE=0.020,  $t(3067)=36.008$ ,  $p<0.001$  using professional fact-checker ratings;  $b=-0.565$ , 95% CI=[-0.613,-0.518], SE=0.0124,  $t(3067)=-23.387$ ,  $p<0.001$  using crowd ratings), whereas the magnitude of the relationship between estimated ideology and quality of content is reduced

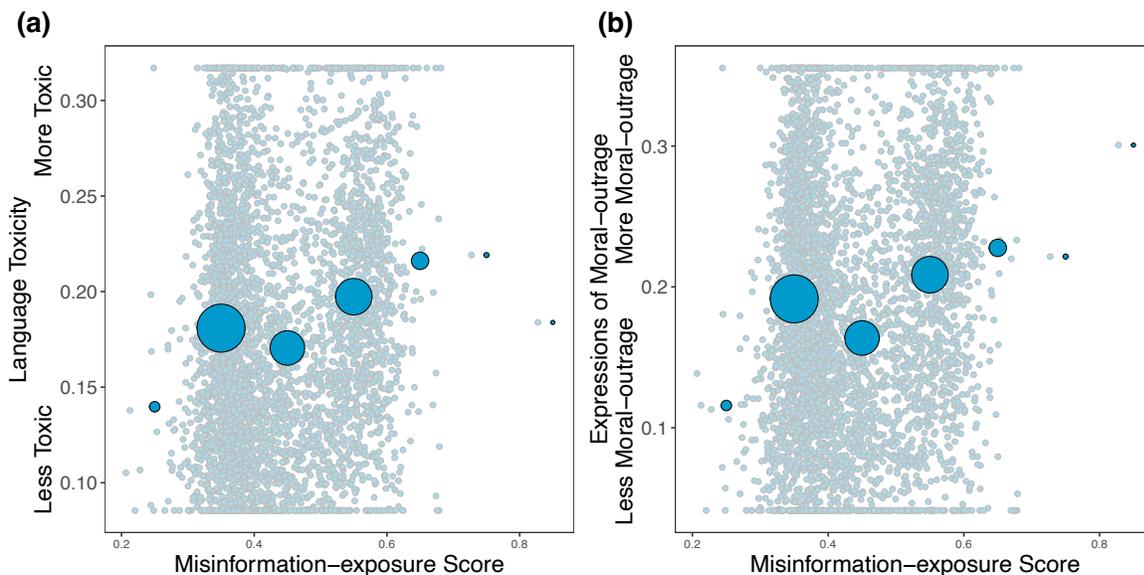
when controlling for misinformation-exposure score ( $b=-0.021$ , 95% CI=[-0.058,0.016], SE=0.019,  $t(3067)=-1.115$ ,  $p=0.265$  using professional fact-checker ratings;  $b=0.030$ , 95% CI=[-0.015,0.076], SE=0.023,  $t(3067)=1.307$ ,  $p=0.191$  using crowd ratings). The coefficient of estimated ideology decreases by almost 100% (from -0.548 to -0.021 using professional fact-checker ratings and from -0.388 to 0.030 using crowd ratings) and becomes insignificant ( $p<0.001$  to  $p=0.265$  using professional fact-checker ratings and  $p<0.001$  to  $p=0.191$  using crowd ratings) when we include misinformation exposure to predict quality of content. Thus, our misinformation exposure score successfully isolates the predictive power of following inaccurate accounts (above and beyond estimated ideology), with misinformation exposure explaining 53% of the variation in the quality of news sources shared when evaluating quality based on fact-checker ratings, and 29% of the variation in the quality of news sources shared when evaluating quality based on crowd ratings.

Given that toxicity and outrage are often associated with online misinformation<sup>25</sup>, we also calculated the average language toxicity using Google Jigsaw Perspective API<sup>26</sup> and the average level of moral-outrage language using a recently published estimator<sup>27</sup>. We found that misinformation-exposure scores are significantly positively related to language toxicity (Figure 3a;  $b=0.129$ , 95% CI=[0.098,0.159], SE=0.015,  $t(4121)=8.323$ ,  $p<0.001$ ;  $b=0.339$ , 95% CI=[0.293,0.384], SE=0.023,  $t(4106)=14.614$ ,  $p<0.001$  when controlling for estimated ideology) and expressions of moral outrage (Figure 3b;  $b=0.107$ , 95% CI=[0.076,0.137], SE=0.015,  $t(4143)=14.243$ ,  $p<0.001$ ;  $b=0.329$ , 95% CI=[0.283,0.374], SE=0.023,  $t(4128)=14.243$ ,  $p<0.001$  when controlling for estimated ideology). See Supplementary Tables 1 and 2 for full regression tables and Supplementary Tables 3–6 for the robustness of our results.

We also note that the list of elites we used here can be used to estimate users' political ideology. To estimate ideology using the list of elites, we code the ideology of democrat elites as -1 and Republican elites as 1, then for each user we average over the ideology of the elites they follow. Our measure of estimated ideology is correlated with the follower-based ideology estimators of ref<sup>10</sup> ( $r=0.86$ , 95% CI=[0.855,0.870],  $t(4330)=112.45$ ,  $p<0.001$ ).



**Figure 2. Exposure to elite misinformation is associated with sharing news from lower quality outlets and with conservative estimated ideology.** Shown is the relationship between users' misinformation-exposure scores and (a) the quality of the news outlets they shared content from, as rated by professional fact-checkers<sup>21</sup>, (b) the quality of the news outlets they shared content from, as rated by layperson crowds<sup>21</sup>, and (c) estimated political ideology, based on the ideology of the accounts they follow<sup>10</sup>. Small dots in the background show individual observations; large dots show the average value across bins of size 0.1, with size of dots proportional to the number of observations in each bin. Source data are provided as a Source Data file.



**Figure 3. Exposure to elite misinformation is associated with the use of toxic language and moral outrage.** Shown here is the relationship between users' misinformation-

*exposure scores and (a) the toxicity of the language used in their tweets, measured using the Google Jigsaw Perspective API<sup>26</sup>, and (b) the extent to which their tweets involved expressions of moral outrage, measured using the algorithm from ref<sup>27</sup>. Extreme values are winsorized by 95% quantile for visualization purposes. Small dots in the background show individual observations; large dots show the average value across bins of size 0.1, with size of dots proportional to the number of observations in each bin. Source data are provided as a Source Data file.*

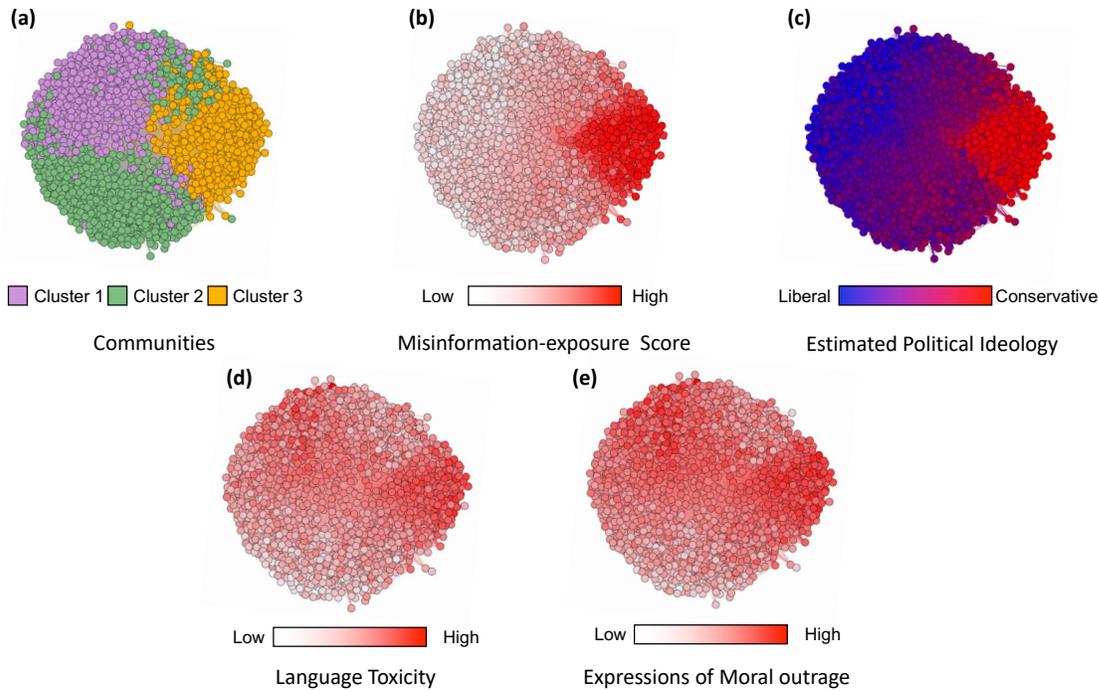
### ***Misinformation-exposure score and co-share network***

Next, we gain more insight into the correlates of misinformation exposure by investigating which domains are preferentially shared by users with higher versus lower misinformation-exposure scores (for similar analysis on co-follower and co-retweet networks, see Supplementary Figures 1 and 2 and Supplementary Tables 7–10). To do so, we constructed a co-share network (see the Methods Section) of the 1,798 domains that were shared by at least 20 users in our sample.

Community-detection analysis<sup>28</sup> on the co-share network reveals three distinct clusters of domains (Figure 4a). Table 1 shows the 10 domains that are shared by the largest number of users in our sample in each cluster. The clusters differ in the average misinformation-exposure scores of users who shared them (Figure 4b; average misinformation-exposure scores of users who shared domains in each cluster are cluster 1, 0.389; cluster 2, 0.404; cluster 3, 0.506), as well as their estimated ideology (Figure 4c; average estimated ideology scores of each cluster are cluster 1, -0.470; cluster 2, 0.038; cluster 3, 1.22). Specifically, we see a cluster of domains estimated to be liberal, a cluster of center-left domains, and a cluster of domains estimated to be conservative, with misinformation exposure higher in the cluster of accounts estimated to be conservative compared to the other two clusters. Importantly, average misinformation-exposure scores of users who shared those domains differed significantly across clusters, even when controlling for average estimated ideology score ( $p < 0.001$  with and without ideology control, Tukey's Honestly Significant Differences test).

Additionally, the clusters differ in the average toxicity of language use (Figure 4d; average toxicity of language use of users who shared domains in each cluster are cluster 1, 0.186; cluster 2, 0.159; cluster 3, 0.199) and moral-outrage expressions (Figure 4e; average moral-outrage expressions in each cluster are cluster 1, 0.213; cluster 2, 0.170; cluster 3, 0.226) of the users who shared the domains, such that the users of the politically centered cluster are less likely to use toxic and moral-outrage language compared to the clusters estimated to be liberal or conservative ( $p < 0.001$  with and without ideology control, Tukey's Honestly Significant Differences test).

We found qualitatively similar results investigating the co-follower and co-retweet networks (see Supplementary Figures 1 and 2 and Supplementary Tables 7–10).



**Figure 4. Members of conservative clusters in the co-share network have higher elite misinformation-exposure scores.** Nodes represent website domains shared by at least 20 users in our dataset and edges are weighted based on common users who shared them. (a) Separate colors represent different clusters using community-detection algorithms<sup>28</sup>. (b) The intensity of the color of each node shows the average misinformation-exposure score of users who shared from the website domain (darker = higher PolitiFact score). (c) Nodes' Color represents the average estimated ideology of the users who shared from the website domain (red: conservative, blue: liberal). (d) The intensity of the color of each node shows the average use of language toxicity (darker = higher use of toxic language). (e) The intensity of the color of each node shows the average expression of moral outrage by users who shared from the website domain (darker = higher expression of moral outrage). Nodes are positioned using directed-force layout on the weighted network.

*Table 1. Top website domains in each cluster within the co-share network. For each cluster, the table shows the 10 website domains in each cluster with the largest number of users who shared them in our sample in descending order. Source data are provided as a Source Data file.*

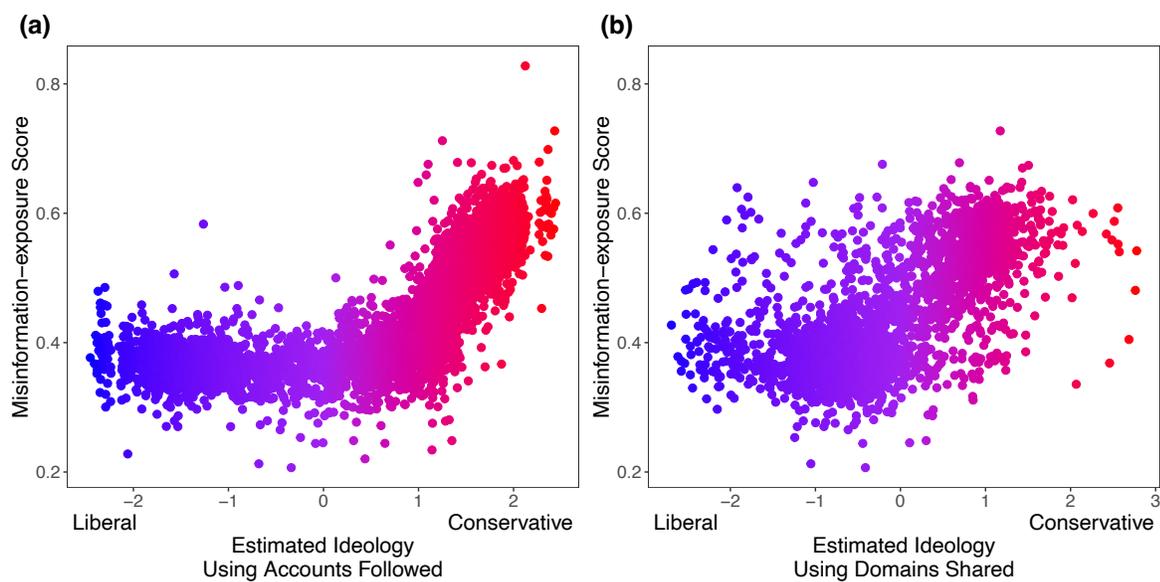
<b>Cluster 1</b>	<b>Cluster 2</b>	<b>Cluster 3</b>
nytimes.com	forbes.com	wsj.com
washingtonpost.com	apple.com	thehill.com
cnn.com	bbc.com	foxnews.com
politico.com	wordpress.com	pscp.tv
nbcnews.com	bbc.co.uk	nypost.com
go.com	espn.com	dailymail.co.uk
huffpost.com	change.org	washingtonexaminer.com
npr.org	vimeo.com	breitbart.com
yahoo.com	eventbrite.com	whitehouse.gov
cbsnews.com	twimg.com	senate.gov

### ***Estimated ideological extremity and misinformation exposure***

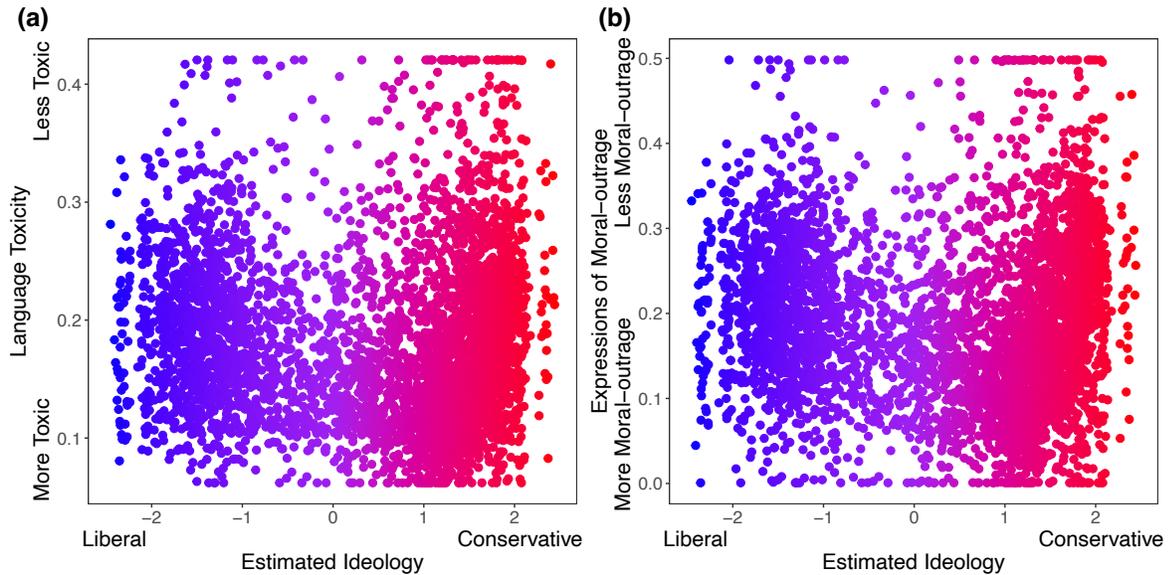
Finally, we complement the co-follower and co-share network analyses with a user-level analysis examining the relationship between estimated ideological extremity and misinformation exposure. To do so, we predict misinformation-exposure scores of the users

in our sample using their estimated ideological extremity (i.e., absolute value of estimated ideology) interacted with binary estimated ideology (liberal versus conservative). We do this analysis using two different methods for robustness: (i) As in the rest of the paper, we use political ideology estimated from the political accounts users follow<sup>10</sup> and discretize based on scores above vs below 0; and (ii) we estimate users' ideology based on their media sharing<sup>29</sup> and use the estimated ideology of the Associated Press (AP; a neutral outlet) as the cut-off (with users who share content that is on average more liberal than AP classified as liberal, and users who share content that is on average more conservative than AP classified as conservative).

We find that more ideologically extreme users are exposed to more misinformation – but, interestingly, this association is stronger among users estimated to be conservative compared to users estimated to be liberal. Specifically, we find a significant interaction between estimated conservative ideology and estimated ideological extremity (Figure 5;  $b = 0.756$ , 95% CI=[0.726,0.786], SE=0.015,  $t(4330)=49.871$ ,  $p < 0.001$  when estimating ideology using accounts followed and  $b = 0.415$ , 95% CI=[ 0.367,0.462], SE= 0.024,  $t(3100)= 17.101$ ,  $p < 0.001$  when estimating ideology using news media sharing). Decomposing this interaction, we find a stronger association between estimated ideological extremity and misinformation exposure among users estimated to be conservative ( $b=0.825$ , 95% CI=[0.804,0.846], SE= 0.010,  $t(2852)= 77.97$ ,  $p < 0.001$  when estimating ideology using accounts followed and  $b=0.567$ , 95% CI=[0.523,0.610], SE=0.022,  $t(1381)=25.508$ ,  $p < 0.001$  when estimating ideology using news media sharing) than users estimated to be liberal ( $b=0.160$ , 95% CI=[0.110,0.211], SE=0.025,  $t(1478)= 6.255$ ,  $p < 0.001$  when estimating ideology using accounts followed and  $b=0.111$ , 95% CI=[0.065,0.159], SE= 0.023,  $t(1719)= 4.659$ ,  $p < 0.001$  when estimating ideology using news media sharing). See Supplementary Table 11 for the full regression. We find a similar asymmetry when using language toxicity or moral outrage as the outcome, rather than misinformation-exposure score (see Figure 6 and Supplementary Table 12).



*Figure 5. Estimated ideological extremity is associated with higher elite misinformation-exposure scores for estimated conservatives more so than estimated liberals. (a) Political ideology is estimated using accounts followed<sup>10</sup>. (b) Political ideology is estimated using domains shared<sup>29</sup> (Red: conservative, blue: liberal). Source data are provided as a Source Data file.*



*Figure 6. Estimated ideological extremity is associated with higher language toxicity and moral outrage scores for estimated conservatives more so than estimated liberals. The relationship between estimated political ideology and (a) language toxicity and (b) expressions of moral outrage. Extreme values are winsorized by 95% quantile for visualization purposes. Source data are provided as a Source Data file.*

## Discussion

In this work, we have introduced an approach to classifying Twitter users' exposure to misinformation from elites based on PolitiFact fact-checks of the accounts they choose to follow. We found that users who followed elites who made more false or inaccurate statements themselves shared news from lower-quality news outlets (as judged by both fact-checkers and a crowd of laypeople), used more toxic language, and expressed more moral outrage. We also found that such users were more likely to be conservative, but that all the above associations were robust to controlling for estimated ideology. At the ecosystem level, we identified a cluster of accounts that tended to be followed by, and domains that tended to be shared by, users who were estimated to be more conservative and who followed less elites who made more false or inaccurate statements. And finally, at the individual level, we found that estimated ideological extremity was more strongly associated with following elites who made more false or inaccurate statements among users estimated to be conservatives compared to users estimated to be liberals. These results on political asymmetries are aligned with prior work on news-based misinformation sharing<sup>30</sup>.

Our findings highlight the importance of the information people choose to expose themselves to when it comes to the spread of misinformation on social media. People who followed elites who made more false or inaccurate statements also shared news from lower-quality sources. This observation connects to research suggesting that political leaders’ rhetoric can drive the beliefs and policy positions of their followers (rather than the leaders responding to the attitudes held by their constituents)<sup>31-33</sup>. It seems reasonable to hypothesize that following elites who make more false or inaccurate statements will cause citizens to believe more misinformation – future work should investigate this possibility. Furthermore, although misinformation exposure may sound like a passive process, in which users are incidentally or unintentionally exposed to misinformation, users on Twitter and other social media platforms have a substantial amount of control over what information they see. In particular, users in our study with high misinformation-exposure scores chose to follow accounts of elites that make false claims. The misinformation score we introduce here can thus be used in future work to examine predictors of which users select into following accounts of elites who make more false or inaccurate statements, as well as to distinguish the role of algorithmic recommendations versus individual user preferences.

Our analysis of co-follower and co-share networks suggests that the phenomenon of echo chambers, in which discourse is more likely with like-minded others, is not limited to politics. We also find evidence of “falsehood echo chambers”, where users that are more often exposed to misinformation are more likely to follow a similar set of accounts and share from a similar set of domains. These results are interesting in the context of evidence that political echo chambers are not prevalent, as typically imagined<sup>34</sup>. While the average American may be fairly politically apathetic and exposed to a broad spectrum of news<sup>34,35</sup>, our results suggest that people who follow politicians on Twitter – and thus are likely to be more politically engaged than the average American – may indeed have more siloed exposure, when it comes to both partisan lean and level of misinformation. Furthermore, our results add to the growing body of literature documenting – at least at this historical moment – the link between extreme right-wing ideology and misinformation<sup>8,14,23</sup> (although, of course, factors other than ideology are also associated with misinformation sharing, such as polarization<sup>24</sup> and inattention<sup>17,36</sup>).

More generally, understanding the role of misinformation originating from cultural and political elites is of the utmost importance, given the influence that elites have on the attitudes of the masses. The approach we have introduced here offers a tool for exploring these issues across a range of applications. To that end, we have built an R package and an API that calculates misinformation-exposure scores and the number of rated elite accounts followed for any set of Twitter users, and have posted the full set of falsity ratings and code online (both are publicly and freely available at <https://github.com/mmosleh/minfo-exposure>). When using this tool, researchers must decide how to handle the misinformation-exposure scores of users who follow only one or two rated accounts and may wish to weight

their models by the precision of the misinformation-exposure score estimates. The tool we developed in this paper is designed to measure users' exposure to misinformation from political elites on Twitter. The tool can be used in scientific research for the purpose of quantifying the quality of content users experience on Twitter. Careful consideration of ethical and privacy issues should be considered in any future use of this research.

There are, of course, important limitations of the present work. Most notably, the misinformation-exposure score we calculate is based on the evaluations of the organization PolitiFact. Thus, to the extent that there is bias in which public figures and statements PolitiFact decides to fact-check, or in PolitiFact's evaluations, those biases will be carried forward into our ratings. For example, the partisan differences in falsity scores associated with elites Twitter accounts and misinformation exposure that we find could be explained, at least in part, by liberal bias on the part of PolitiFact in which claims they evaluate and what conclusions they reach<sup>37,38</sup>. It is somewhat reassuring, however, that the misinformation-exposure scores we calculate are correlated with sharing links to low-quality news sites as judged not just by fact-checkers but also by politically balanced layperson crowds. Furthermore, the basic methodology we have introduced can be extended to use falsity ratings from any source, such as other fact-checking organizations (e.g., right-leaning sites such as TheDispatch.com) or crowd ratings (e.g., Twitter's Birdwatch program<sup>39</sup>). Another limitation of our approach is that users must follow a sufficient number of elite accounts in order to receive a misinformation-exposure score. Future work should investigate what user characteristics are predictive of following these elite accounts, and thus what forms of selection are induced by restricting to users who follow these elite accounts. Furthermore, our approach relies on users' immediate follower network and does not capture exposure beyond one's followed account (e.g., through retweets by users one is connected to, or by algorithmic recommendations). Relatedly, when assessing the association between exposure to elite misinformation and misinformation sharing, the measure of sharing quality that we used was able to assign quality ratings to only a small subset of links; future work should generalize these analyses to other misinformation-sharing metrics. Finally, our focus here is on Twitter, which is not a representative sample of the population; however, the approach we introduce here could be used on any other social media platform in which one can observe which pages or accounts a given user follows.

The approach we have introduced here opens new doors to understanding the role of exposure to misinformation from elites, and choices about who to follow online, in the spread of false and misleading claims over social media.

## **Methods**

### *Data collection*

We retrieved ratings for all 1005 elites (e.g., politicians, bureaucrats, famous personalities, advocacy groups, and media organizations) that, as of October 28, 2020, were fact-checked at least three times by the fact-checking website PolitiFact (restricting to those with at least four fact-checks gives similar results; see Supplementary Figure 3). Each fact-check results in one of six ratings assigned by PolitiFact: True (the statement is accurate and there is nothing significant missing), Mostly True (the statement is accurate but needs clarification or additional information), Half True (the statement is partially accurate but leaves out important details or takes things out of context), Mostly False (the statement contains an element of truth but ignores critical facts that would give a different impression), False (the statement is not accurate), and Pants on Fire (the statement is not accurate and makes a ridiculous claim). For each elite, we then calculated a falsity score by assigning each fact-check a veracity rating using the scoring scheme from (True: 1, Mostly True: 0.8, Half True: 0.6, Mostly False: 0.4, False: 0.2, Pants on Fire: 0), averaging the rating of all fact-checks for that figure (creating an average veracity score), and then subtracting that score from 1 to convert from a veracity score to a falsity score. Our results are not unique to this particular scoring scheme (see Supplementary Table 4).

To use these falsity scores to rate Twitter users' exposure to misinformation from elites, we identified 950 Twitter accounts that are associated with 816 of the 1005 elites (we could not find Twitter accounts for the remaining 189 accounts; we found multiple Twitter accounts for some of the 816 and included all of them. Our results are robust excluding entities with multiple Twitter accounts and also excluding entities related to organizations; see Supplementary Table 5). We then collected all of the followers of these 950 accounts ( $N=122,562,681$  unique users). For assessment purposes, we created a list of users who followed at least three elites ( $N=38,328,679$ ) and then randomly sampled  $N=5,000$  Twitter users from that list (see Supplementary Figures 3 and 4 for results when using alternative thresholds for number of accounts followed). For each user in our sample, we calculated the misinformation-exposure score by averaging over the falsity score of all rated elite accounts that the user followed, weighted by the average number of tweets per two-month period in the past two years of the corresponding account as a proxy for intensity of exposure (our findings are robust when falsity scores are not weighted, see Supplementary Table 4; we could not retrieve the list of followed accounts for 650 of the 5,000 users since they were protected accounts or did not exist anymore).

#### *Estimating users' political ideology*

We also estimated the political ideology of users based on accounts they followed<sup>10</sup>. The logic behind this approach is that users on social media are more likely to follow accounts that align with their own ideology than ideologically distant accounts. With the list of partisan elite accounts from ref<sup>10</sup>, we used their algorithm to calculate a continuous ideology

score on the interval  $[-2.5, 2.5]$  for each user, where  $-2.5$  represents a strong liberal ideology and  $2.5$  represents a strong conservative ideology. We used ideology midpoint  $0$  to classify users as conservative versus liberal.

### ***Quantifying quality of content***

Additionally, we quantified the quality of content shared by each user with a list of domains for which we have professional fact-checkers' trustworthiness ratings, similar to prior work<sup>16,17</sup>. We did so by collecting their last 3,200 tweets on July 23, 2021 (capped by the Twitter API limit; we could not retrieve the timeline of 837 out of 5,000 users since they were protected accounts, did have any tweets, or did not exist anymore), identifying all tweets that contained URLs, and averaging the trustworthiness ratings of the news domains each URL linked to. Specifically, we used a list of 60 news websites<sup>21</sup> (20 fake news, 20 hyper-partisan, and 20 mainstream news websites), each of whose trustworthiness had been rated  $[0, 1]$  by eight professional fact-checkers, as well as by a large politically balanced crowd of demographically representative (quota-sampled) laypeople living in the United States recruited via Lucid (the crowd was balanced in terms of its representation of different political ideologies). Of 5,363,779 total links shared by users in our sample, 5% were from the list of news websites for which we had fact-checkers' ratings. For each user, we calculated the quality of content shared by averaging the rated news websites they had shared.

### ***Constructing co-share network***

Finally, following prior work on cognitive echo chambers on social media<sup>13</sup>, we constructed a co-share network where nodes represent domains that are shared by at least 20 users in our sample and weighted edges represent the number of users who mutually shared them. For each domain, we averaged over estimated ideology, misinformation-exposure scores, language toxicity, and expression of moral outrage of users who shared that website. We used a similar approach to construct co-follower (see Supplementary Figure 1; Supplementary Tables 7 and 8) and co-retweet networks (see Supplementary Figure 2; Supplementary Tables 9 and 10).

All statistics reported in the results are conducted using linear regression models with standardized coefficients, unless otherwise stated. All statistical tests are two-tailed. All data were collected using Twitter API and Python. Our study received a waiver from an ethics review by the MIT Committee on the Use of Humans as Experimental Subjects (COUHES) protocol E-3973. In conducting our study, we followed Twitter's terms of use.

## Data Availability

PolitiFact data were obtained in line with the website's Terms of Service and are available in ref<sup>40</sup>. Twitter data contains identifiable information -- and for confidentiality reasons -- are only available upon request. The Twitter data are available under restricted access for research purposes, access can be obtained by writing to the authors. Source data are provided with this paper.

## Code Availability

All code used to generate the results are available on <https://osf.io/5283b/><sup>41</sup>. An R package and an API that calculates misinformation-exposure scores is publicly available at <https://github.com/mmosleh/minfo-exposure>.

## References

- 1 Lazer, D. M. *et al.* The science of fake news. *Science* **359**, 1094-1096 (2018).
- 2 Pennycook, G. & Rand, D. G. The psychology of fake news. *Trends in cognitive sciences* (2021).
- 3 Pennycook, G. & Rand, D. G. Examining false beliefs about voter fraud in the wake of the 2020 Presidential Election. *The Harvard Kennedy School Misinformation Review* (2021).
- 4 Slothuus, R. & Bisgaard, M. How political parties shape public opinion in the real world. *American Journal of Political Science* (2020).
- 5 SLOTHUUS, R. & BISGAARD, M. Party over Pocketbook? How Party Cues Influence Opinion When Citizens Have a Stake in Policy. *American Political Science Review*, 1-7 (2021).
- 6 Levendusky, M. S. Clearer cues, more consistent voters: A benefit of elite polarization. *Political Behavior* **32**, 111-131 (2010).
- 7 Pink, S., Chu, J., Druckman, J., Rand, D. & Willer, R. Elite Party Cues Increase Vaccination Intentions among Republicans. (2021).
- 8 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).
- 9 Pennycook, G., Cannon, T. D. & Rand, D. G. Prior exposure increases perceived accuracy of fake news. *Journal of experimental psychology: general* **147**, 1865 (2018).
- 10 Barberá, P., Jost, J. T., Nagler, J., Tucker, J. A. & Bonneau, R. Tweeting from left to right: Is online political communication more than an echo chamber? *Psychological science* **26**, 1531-1542 (2015).
- 11 Vosoughi, S., Roy, D. & Aral, S. The spread of true and false news online. *Science* **359**, 1146-1151 (2018).
- 12 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).
- 13 Mosleh, M., Pennycook, G., Arechar, A. A. & Rand, D. G. Cognitive reflection correlates with behavior on Twitter. *Nature communications* **12**, 1-10 (2021).
- 14 Guess, A., Nagler, J. & Tucker, J. Less than you think: Prevalence and predictors of fake news dissemination on Facebook. *Science advances* **5**, eaau4586 (2019).
- 15 Guess, A. M., Nyhan, B. & Reifler, J. Exposure to untrustworthy websites in the 2016 US election. *Nature human behaviour* **4**, 472-480 (2020).
- 16 Mosleh, M., Martel, C., Eckles, D. & Rand, D. G. in *proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. 1-13.

- 17 Pennycook, G. *et al.* Shifting attention to accuracy can reduce misinformation online. *Nature* **592**, 590-595 (2021).
- 18 Bakshy, E., Eckles, D. & Bernstein, M. S. in *Proceedings of the 23rd international conference on World wide web*. 283-292.
- 19 Guess, A. M. Experiments Using Social Media Data. *Advances in Experimental Political Science*, 184 (2021).
- 20 Mosleh, M., Pennycook, G. & Rand, D. G. Field experiments on social media. *Current Directions in Psychological Science* **31**, 69-75 (2022).
- 21 Pennycook, G. & Rand, D. G. Fighting misinformation on social media using crowdsourced judgments of news source quality. *Proceedings of the National Academy of Sciences* **116**, 2521-2526 (2019).
- 22 Allcott, H. & Gentzkow, M. Social media and fake news in the 2016 election. *Journal of economic perspectives* **31**, 211-236 (2017).
- 23 Garrett, R. K. & Bond, R. M. Conservatives' susceptibility to political misperceptions. *Science Advances* **7**, eabf1234 (2021).
- 24 Osmundsen, M., Bor, A., Vahlstrup, P. B., Bechmann, A. & Petersen, M. B. Partisan polarization is the primary psychological motivation behind political fake news sharing on Twitter. *American Political Science Review* **115**, 999-1015 (2021).
- 25 McLoughlin, K. L., Brady, W. J. & Crockett, M. J. The role of moral outrage in the spread of misinformation. *TMS Proceedings* (2021).
- 26 Jigsaw. Perspective API.
- 27 Brady, W. J., McLoughlin, K., Doan, T. N. & Crockett, M. J. How social learning amplifies moral outrage expression in online social networks. *Science Advances* **7**, eabe5641 (2021). <https://doi.org/doi:10.1126/sciadv.abe5641>
- 28 Blondel, V. D., Guillaume, J.-L., Lambiotte, R. & Lefebvre, E. Fast unfolding of communities in large networks. *Journal of statistical mechanics: theory and experiment* **2008**, P10008 (2008).
- 29 Eady, G., Nagler, J., Guess, A., Zilinsky, J. & Tucker, J. A. How many people live in political bubbles on social media? Evidence from linked survey and Twitter data. *Sage Open* **9**, 2158244019832705 (2019).
- 30 Nikolov, D., Flammini, A. & Menczer, F. Right and left, partisanship predicts (asymmetric) vulnerability to misinformation. *Harvard Kennedy School (HKS) Misinformation Review* (2021).
- 31 Berinsky, A. J. in *In Time of War* (University of Chicago Press, 2009).
- 32 Lenz, G. S. *Follow the leader?: how voters respond to politicians' policies and performance*. (University of Chicago Press, 2013).
- 33 Zaller, J. R. *The nature and origins of mass opinion*. (Cambridge university press, 1992).
- 34 Guess, A. M. (Almost) Everything in Moderation: New Evidence on Americans' Online Media Diets. *American Journal of Political Science* **65**, 1007-1022 (2021).
- 35 Converse, P. E. Assessing the capacity of mass electorates. *Annual review of political science* **3**, 331-353 (2000).
- 36 Pennycook, G., McPhetres, J., Zhang, Y., Lu, J. G. & Rand, D. G. Fighting COVID-19 misinformation on social media: Experimental evidence for a scalable accuracy-nudge intervention. *Psychological science* **31**, 770-780 (2020).
- 37 Marietta, M., Barker, D. C. & Bowser, T. in *The Forum*. 577-596 (De Gruyter).
- 38 Farnsworth, S. J. & Lichter, S. R. in *American Political Science Association Annual Meeting, Philadelphia, PA, September*.
- 39 Birdwatch. Today, we're updating how notes are elevated in Birdwatch! This change will give more weight to contributors whose notes and ratings are consistently found helpful by others, <<https://twitter.com/birdwatch/status/1404519791394758657>> (2021).
- 40 Golding, B. *PolitiFact: Pols, Pundits, and Pant Fires*, <<https://iffy.news/2020/politifact-pols-pundits-and-pant-fires/>> (2020).
- 41 Mosleh, M. & Rand, D. G. *Measuring exposure to misinformation from political elites on Twitter*, <<https://osf.io/5283b/>> (2022).

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### **Author Contributions Statement**

MM and DGR designed the research. MM accessed PolitiFact data and Twitter data. MM conducted the analysis. MM and DGR wrote the paper.

### **Competing Interests Statement**

MM and D.R. have received research funding from Google, and D.R. has received research funding from Meta.

*Supplementary Information*

**Measuring exposure to misinformation from  
political elites on Twitter**

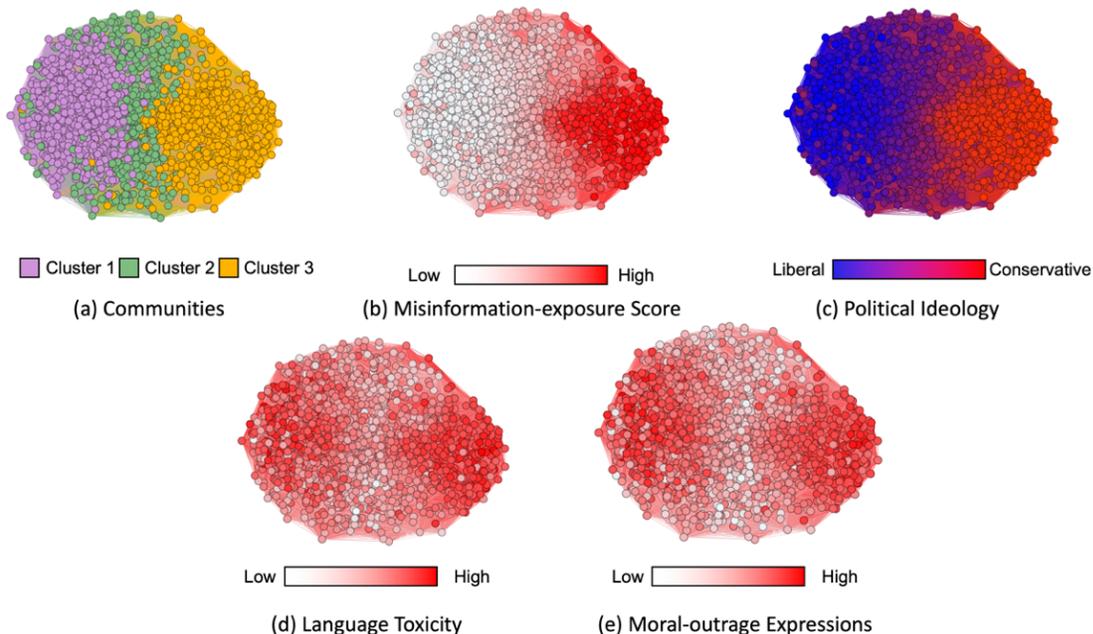
Mohsen Mosleh\*

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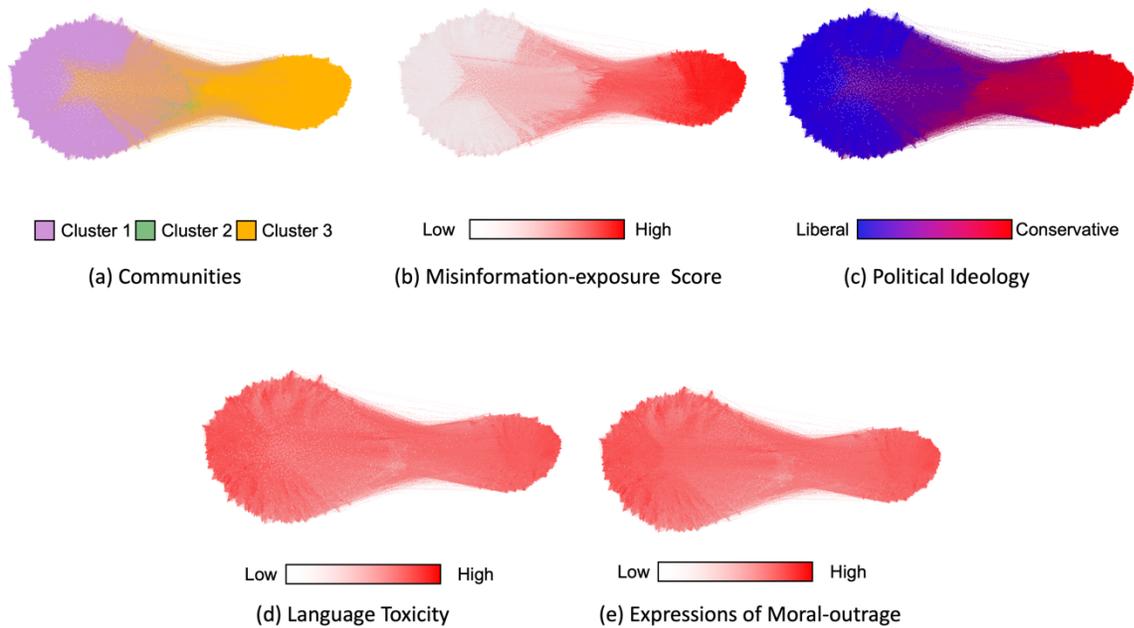
David G. Rand

Sloan School of Management, Massachusetts Institute of Technology, Institute for Data, Systems, and Society, Massachusetts Institute of Technology, Department of Brain and Cognitive Sciences, Massachusetts Institute of Technology, United States, drand@mit.edu

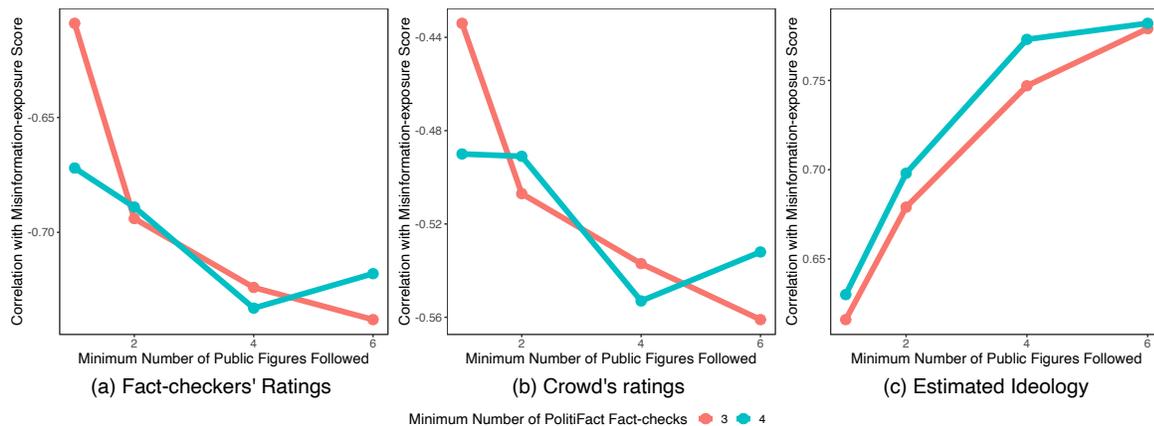
## 1 SUPPLEMENTARY FIGURES



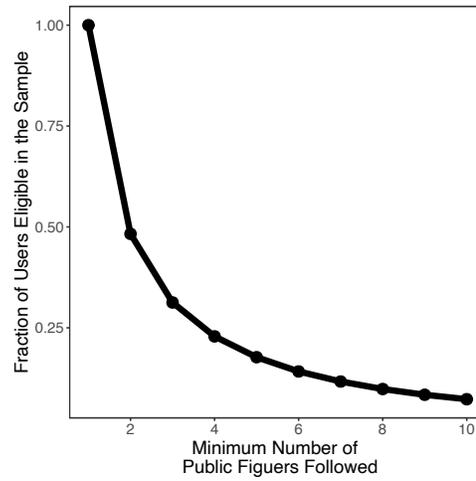
**Supplementary Figure 1. Co-follower network.** Nodes represent Twitter accounts followed by at least 200 users in our dataset and edges are weighted based on common followers. (a) Separate colors represent different clusters using community detection algorithms [1]. (b) The intensity of color of each node shows the average misinformation-exposure score of its followers (darker = higher misinformation-exposure score). (c) Nodes' color represents the average estimated ideology of the followers (red: conservative, blue: liberal). (d) Average language toxicity used by the followers (darker = more toxic language use). (e) Average moral-outrage expressions (darker = more expressions of moral-outrage). Nodes are positioned using directed-force layout based on the weighted network. See Supplementary Table 7 for average characteristics of users who followed accounts in each cluster and Supplementary Table 8 for top 10 accounts in each cluster.



**Supplementary Figure 2. Co-retweet network.** Nodes represent Twitter accounts retweeted by at least 20 users in our dataset and edges are weighted based on the number of common users who retweeted those accounts. (a) Separate colors represent different clusters using community detection algorithms [1]. (b) The intensity of color of each node shows the average misinformation-exposure score of the users who retweeted the accounts (darker = higher misinformation-exposure score). (c) Nodes' color represents the average estimated ideology of the users who retweeted the accounts (red: conservative, blue: liberal). (d) Average language toxicity used by the users who retweeted the accounts (darker = more toxic language use). (e) Average moral-outrage expressions (darker = more expressions of moral-outrage). Nodes are positioned using directed-force layout based on the weighted network. See Supplementary Table 9 for average characteristics of users who retweeted accounts in each cluster and Supplementary Table 10 for top 10 accounts in each cluster.



**Supplementary Figure 3.** Robustness of results for various minimum number of elite accounts followed and minimum number of fact-checks by PolitiFact. We created separate lists of associated Twitter accounts for public figures with a minimum of 3 versus 4 PolitiFact fact-checks. Next, for each list of accounts, we generated separate random samples of 5,000 Twitter users who follow a minimum number of 1, 2, 4, or 6 falsity-rated accounts. Shown here are Pearson's correlation coefficients between misinformation-exposure score and (a) quality of content shared as measured by professional fact-checkers trustworthiness, (b) quality of content shared as measured by crowd trustworthiness, and (c) estimated political ideology. All correlations are significant ( $p < 0.001$  two-tailed). Across all three panels, while increasing the number of fact-checkers required for public figures or organizations to be included had little effect, increasing the minimum number of public figures followed (and thus increasing the precision of the misinformation-exposure score estimates) yields stronger correlations. Thus, when using this tool, one must make a trade-off between using a lower threshold for the number of followed accounts and being able to determine scores for a larger fraction of users (see Supplementary Figure 4) or using a higher threshold and achieving less noisy estimates for each user. Source data are provided as a Source Data file.



**Supplementary Figure 4.** *Fraction of users within our sample ( $N=122,562,681$ ) for whom we can calculate a Misinformation-exposure Score. Shown here is the fraction of our sample depending on what we set as the minimum number of rated accounts they must follow to be included. Source data are provided as a Source Data file.*

## 2 SUPPLEMENTARY TABLES

**Supplementary Table 1.** Regression models predicting misinformation-exposure score using fact-checkers ratings and crowd's ratings of content users shares and their estimated political ideology. All statistical tests are two-tailed ( $p < .1$ ,  $*p < 0.05$ ,  $**p < 0.01$ ,  $***p < 0.001$ )

	Dependent variable	Independent variable	
<b>Model 1</b>	Fact-checkers ratings	Intercept	-0.037** (0.012)
		Misinformation-exposure score	-0.728*** (0.013)
<b>Model 2</b>	Crowd ratings	Intercept	-0.027 (0.015)
		Misinformation-exposure score	-0.540*** (0.015)
<b>Model 3</b>	Fact-checkers ratings	Intercept	-0.039** (0.013)
		Misinformation-exposure score	-0.712*** (0.020)
		Estimated political ideology	-0.021 (0.019)
<b>Model 4</b>	Crowd ratings	Intercept	-0.026 (0.015)
		Misinformation-exposure score	-0.565*** (0.024)
		Estimated political ideology	0.030 (0.023)
<b>Model 5</b>	Estimated political ideology	Intercept	-0.001 (0.010)
		Misinformation-exposure score	0.747*** (0.010)

**Supplementary Table 2.** Regression models predicting language toxicity and express of moral-outrage using misinformation- exposure score and users' estimated political ideology. All statistical tests are two-tailed ( $p < .1$ ,  $*p < 0.05$ ,  $**p < 0.01$ ,  $***p < 0.001$ )

	<b>Dependent variable</b>	<b>Independent variable</b>	
<b>Model 1</b>	Language toxicity	Intercept	0.002 (0.015)
		Misinformation-exposure score	0.129*** (0.015)
<b>Model 2</b>	Expression of moral outrage	Intercept	0.002 (0.015)
		Misinformation-exposure score	0.107*** (0.023)
<b>Model 3</b>	Language toxicity	Intercept	0.002 (0.015)
		Misinformation-exposure score	0.319*** (0.023)
		Estimated political ideology	-0.246*** (0.023)
<b>Model 4</b>	Expression of moral outrage	Intercept	0.003 (0.015)
		Misinformation-exposure score	0.329*** (0.023)
		Political ideology	-0.290*** (0.023)

**Supplementary Table 3.** Robustness of results using estimating political ideology based on media sharing [2]. Regression models predicting misinformation-exposure score using fact-checkers ratings and crowd's ratings of content users shares and their estimated political ideology using media sharing. All statistical tests are two-tailed. ( $p < .1$ ,  $*p < 0.05$ ,  $**p < 0.01$ ,  $***p < 0.001$ )

	Dependent variable	Independent variable	Estimating political ideology using accounts followed	Estimating political ideology using media sharing
Model 1	Fact-checkers ratings	Intercept	-0.037** (0.012)	-0.037** (0.012)
		Misinformation-exposure score	-0.728*** (0.013)	-0.728*** (0.013)
Model 2	Crowd ratings	Intercept	-0.027 (0.015)	-0.027 (0.015)
		Misinformation-exposure score	-0.540*** (0.015)	-0.540*** (0.015)
Model 3	Fact-checkers ratings	Intercept	-0.039** (0.013)	-0.027 (0.012)
		Misinformation-exposure score	-0.712*** (0.02)	-0.457*** (0.017)
		Political ideology	-0.021 (0.019)	-0.373*** (0.017)
Model 4	Crowd ratings	Intercept	-0.026 (0.015)	-0.014 (0.015)
		Misinformation-exposure score	-0.565*** (0.024)	-0.366*** (0.022)
		Political ideology	0.03 (0.023)	-0.242*** (0.022)
Model 5	Political ideology	Intercept	-0.001 (0.010)	-0.05*** (0.013)
		Misinformation-exposure score	0.746*** (0.010)	0.695*** (0.013)

**Supplementary Table 4.** Robustness of results for various functional forms mapping fact-checking categories to veracity scores. Mapping function 1 used in the main text: (True, Mostly True, Half True, Mostly False, False, Pants on Fire) = (5/5, 4/5, 3/5, 2/5, 1/5, 0), Mapping function 2 (True, Mostly True, Half True, Mostly False, False, Pants on Fire) = (1, 1, 0.5, 0, 0, 0); Mapping function 3 (True, Mostly True, Half True, Mostly False, False, Pants on Fire) = (1, 1, 0, 0, 0, 0); Mapping function 4 similar to the main text but not weighted by number of tweets of the public figure : (True, Mostly True, Half True, Mostly False, False, Pants on Fire) = (5/5, 4/5, 3/5, 2/5, 1/5, 0); Results shown are the coefficient and p-value of linear regression models predicting misinformation-exposure scores. All statistical tests are two-tailed.

All mapping functions are weighted by the number tweets made by the elites except mapping function 4. ( $p < .1$ ,  $*p < 0.05$ ,  $**p < 0.01$ ,  $***p < 0.001$ )

	Dependent variable	Independent variable	Mapping function 1	Mapping function 2	Mapping function 3	Mapping function 4
<b>Model 1</b>	Fact-checkers ratings	Intercept	-0.037** (0.012)	-0.04** (0.013)	-0.038** (0.013)	-0.042** (0.012)
		Misinformation-exposure score	-0.728*** (0.013)	-0.714*** (0.013)	-0.726*** (0.013)	-0.73*** (0.012)
<b>Model 2</b>	Crowd ratings	Intercept	-0.027 (0.015)	-0.03 (0.015)	-0.028 (0.015)	-0.031 (0.015)
		Misinformation-exposure score	-0.54*** (0.015)	-0.527*** (0.016)	-0.537*** (0.015)	-0.543*** (0.015)
<b>Model 3</b>	Fact-checkers ratings	Intercept	-0.039** (0.013)	-0.046*** (0.013)	-0.04** (0.013)	-0.041** (0.012)
		Misinformation-exposure score	-0.712*** (0.02)	-0.647*** (0.019)	-0.714*** (0.02)	-0.76*** (0.02)
		Political ideology	-0.021 (0.019)	-0.086*** (0.019)	-0.016 (0.019)	0.036 (0.02)
<b>Model 4</b>	Crowd ratings	Intercept	-0.026 (0.015)	-0.032 (0.015)	-0.027 (0.015)	-0.028 (0.015)
		Misinformation-exposure score	-0.565*** (0.024)	-0.508*** (0.024)	-0.565*** (0.025)	-0.61*** (0.025)
		Political ideology	0.03 (0.023)	-0.025 (0.022)	0.033 (0.023)	0.08** (0.024)
<b>Model 5</b>	Political ideology	Intercept	-0.001 (0.010)	0.001 (0.010)	0.001 (0.010)	0.001 (0.010)
		Misinformation-exposure score	0.746*** (0.010)	0.728*** (0.010)	0.755*** (0.010)	0.772*** (0.010)

**Supplementary Table 5.** Robustness of results when including only Twitter accounts related to public political figures (excluding accounts related to organizations) and when excluding elites with multiple Twitter accounts. To identify news organizations, we used type of the elite from the PolitiFact data and only included elites classified as “person”. Results shown are the coefficient and p-value of linear regression models predicting misinformation-exposure scores. All statistical tests are two-tailed. ( $p < .1$ ,  $*p < 0.05$ ,  $**p < 0.01$ ,  $***p < 0.001$ ).

	Dependent variable	Independent variable	Not Excluding anyone	Excluding news organizations' Twitter accounts	Excluding elites with multiple Twitter accounts
<b>Model 1</b>	Fact-checkers ratings	Intercept	-0.037** (0.012)	-0.038** (0.013)	-0.036** (0.013)
		Misinformation-exposure score	-0.728*** (0.013)	-0.71*** (0.013)	-0.721*** (0.013)
<b>Model 2</b>	Crowd ratings	Intercept	-0.027 (0.015)	-0.028 (0.015)	-0.027 (0.015)
		Misinformation-exposure score	-0.54*** (0.015)	-0.519*** (0.015)	-0.533*** (0.016)
<b>Model 3</b>	Fact-checkers ratings	Intercept	-0.039** (0.013)	-0.04** (0.013)	-0.04** (0.013)
		Misinformation-exposure score	-0.712*** (0.02)	-0.689*** (0.021)	-0.684*** (0.02)
		Political ideology	-0.021 (0.019)	-0.026 (0.02)	-0.049 (0.019)
<b>Model 4</b>	Crowd ratings	Intercept	-0.026 (0.015)	-0.028 (0.016)	-0.027 (0.015)
		Misinformation-exposure score	-0.565*** (0.024)	-0.531*** (0.025)	-0.539*** (0.024)
		Political ideology	0.03 (0.023)	0.014 (0.024)	0.006 (0.023)
<b>Model 5</b>	Political ideology	Intercept	-0.001 (0.010)	-0.001 (0.01)	0 (0.010)
		Misinformation-exposure score	0.746*** (0.010)	0.759*** (0.010)	0.737*** (0.010)

**Supplementary Table 6.** Correlation of quality of content shared and misinformation exposures score with users' characteristics. Results shown are the coefficient of Pearson correlation. All statistical tests are two-tailed. All correlations are significant ( $p < 0.001$  Pearson correlation). The magnitude of correlations for misinformation exposure score are significantly different from those for fact-checkers ratings and crowd ratings ( $p < 0.001$  using confidence intervals to compare correlations; [3]).

	Estimated political ideology	Use of toxic language	Expressions of moral outrage
<b>Misinformation exposure score</b>	0.75	0.13	0.11
<b>Misinformation sharing (fact-checker ratings)</b>	-0.57	-0.25	-0.25
<b>Misinformation sharing (crowd ratings)</b>	-0.40	-0.19	-0.20

**Supplementary Table 7.** Average characteristics of users who followed accounts in each cluster in the co-follower network. Misinformation-exposure score, use of toxic language, expression of moral-outrage differed significantly across clusters, even when controlling for average ideology score ( $p < 0.001$  with and without ideology control, Tukey Honest Significant Differences test; all statistical tests are two-tailed).

	Number of nodes in cluster	Estimated political ideology	Misinformation exposure score	Use of toxic language	Expressions of moral-outrage
<b>Cluster 1</b>	898	-0.475	0.3767	0.1953	0.2162
<b>Cluster 2</b>	404	0.279	0.4104	0.1782	0.1779
<b>Cluster 3</b>	555	1.4266	0.5102	0.1997	0.2161

**Supplementary Table 8. Top accounts in each cluster within the co-follower network.** For each cluster the table shows the 10 accounts in each cluster with the largest number of followers amongst our sample in descending order. Source data are provided as a Source Data file.

Cluster 1	Cluster 2	Cluster 3
Barack Obama	The New York Times	The White House 45 Archived
Joe Biden	The Associated Press	President Trump 45 Archived
Hillary Clinton	The Washington Post	Melania Trump 45 Archived
Kamala Harris	CNN	Vice President Mike Pence Archived
Nancy Pelosi	CNN Breaking News	Kayleigh McEnany 45 Archived
Elizabeth Warren	The Wall Street Journal	Fox News
Rachel Maddow MSNBC	Bill Clinton	Ted Cruz
Bernie Sanders	BBC Breaking News	Sean Hannity
Elizabeth Warren	BBC News (World)	Ivanka Trump

**Supplementary Table 9.** Average characteristics of users who retweeted accounts in each cluster in the co-retweet network. Misinformation-exposure score, use of toxic language, expression of moral-outrage differed significantly across clusters, even when controlling for average ideology score ( $p < 0.001$  with and without ideology control, Tukey Honest Significant Differences test; all statistical tests are two-tailed)

	Number of nodes in cluster	Estimated political ideology	Misinformation exposure score	Use of toxic language	Expressions of moral-outrage
<b>Cluster 1</b>	3,996	-0.829	0.370	0.204	0.239
<b>Cluster 2</b>	159	0.348	0.422	0.169	0.175
<b>Cluster 3</b>	2,035	1.54	0.534	0.210	0.243

**Supplementary Table 10.** Top accounts in each cluster within the co-retweet network. For each cluster the table shows the 10 accounts in each cluster with the largest number of followers amongst our sample in descending order.

Cluster 1	Cluster 2	Cluster 3
The New York Times	The Hill	The White House
CNN	SportsCenter	Charlie Kirk
The Washington Post	ESPN	Fox News
Barack Obama	Bleacher Report	Donald Trump Jr.
ABC News	Mashable	James Woods,
Kyle Griffin	MLB	ULTRA POSO
Joe Biden	AFP News Agency	Ted Cruz
NBC News	Darren Rovell	The Wall Street Journal
The Associated Press	Adam Schefter	Ryan Fournier

**Supplementary Table 11.** Regression model predicting misinformation-exposure score using estimated extremity of political ideology, political ideology (0: Liberal, 1: Conservative), and their interaction.

	Estimated Ideology using accounts followed	Estimated Ideology using media shared
<b>Intercept</b>	-0.824*** (0.012)	-0.640*** (0.016)
<b>Estimated Extremity</b>	0.050** (0.012)	0.070*** (0.018)
<b>Ideology (1:Conservative)</b>	1.22*** (0.015)	1.175*** (0.024)
<b>Estimated Extremity X Estimated Ideology</b>	0.756*** (0.015)	0.415*** (0.024)

**Supplementary Table 12 .** Regression model predicting (a) language toxicity and (b) expressions of moral outrage using estimated political ideology extremity, political ideology (0: Liberal, 1: Conservative), and their interaction.

	<b>Language toxicity</b>	<b>Expressions of moral outrage</b>
<b>Intercept</b>	0.099** (0.026)	0.143*** (0.025)
<b>Estimated Extremity</b>	0.109** (0.025)	0.131*** (0.025)
<b>Estimated Ideology: Conservative</b>	-0.150*** (0.032)	-0.216*** (0.032)
<b>Estimated Extremity X Estimated Ideology</b>	0.100** (0.032)	0.105*** (0.031)

## SUPPLEMENTARY REFERENCES

- [1] Blondel, V. D., Guillaume, J.-L., Lambiotte, R. and Lefebvre, E. Fast unfolding of communities in large networks. *Journal of statistical mechanics: theory and experiment*, 2008, 10 (2008), P10008.
- [2] Eady, G., Nagler, J., Guess, A., Zilinsky, J. and Tucker, J. A. How many people live in political bubbles on social media? Evidence from linked survey and Twitter data. *Sage Open*, 9, 1 (2019), 2158244019832705.
- [3] Zou, G. Y. Toward using confidence intervals to compare correlations. *Psychological methods*, 12, 4 (2007), 399.