Fighting COVID-19 Misinformation on Social Media: Experimental Evidence for a Scalable Accuracy-Nudge Intervention

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Fighting COVID-19 misinformation on social media: Experimental evidence for a scalable accuracy nudge intervention

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Abstract

Across two studies with over 1,600 U.S. adults recruited online, we present evidence that people share false claims about COVID-19 partly because they simply fail to think sufficiently about whether or not content is accurate when deciding what to share. In Study 1, participants were far worse at discerning between true and false content when deciding what they would share on social media relative to when they are asked directly about accuracy. Furthermore, cognitive reflection and science knowledge were associated with stronger discernment. In Study 2, we found that a simple accuracy reminder at the beginning of the study – i.e., judging the accuracy of a non-COVID-19-related headline – more than doubled the level of truth discernment in participants' sharing intentions. Our results, which mirror those found previously for political fake news, suggest that nudging people to think about accuracy is a simple way to improve choices about what to share on social media.

Statement of Relevance

Misinformation can amplify humanity's greatest challenges. A salient example is the COVID-19 pandemic. The environment created by the pandemic has bred a multitude of falsehoods even as truth has become a matter of life-and-death. In this research, we investigated why people believe and spread false (and true) news content about COVID-19. We found that people often fail to consider accuracy when deciding what to share, and they are more likely to believe and share falsehoods if they are more intuitive or less knowledgeable about science. We also tested an intervention to increase the truthfulness of the content shared on social media. Simply prompting people to think about the accuracy of an unrelated headline improved subsequent choices about what COVID-19 news to share. Accuracy nudges are straightforward for social media platforms to implement on top of the other approaches they are currently employing. With further optimization, interventions focused on increasing the salience of accuracy on social media could have a positive impact on countering the tide of misinformation.

"We're not just fighting an epidemic; we're fighting an infodemic,"
-Tedros Adhanom Ghebreyesus, Director-General of the World Health Organization (WHO)

The COVID-19 pandemic represents a substantial challenge to global human wellbeing. Not unlike other challenges (e.g., global warming), the impact of COVID-19 pandemic depends on the actions of individual citizens and, therefore, the quality of the information to which people are exposed. Unfortunately, however, misinformation about COVID-19 has proliferated, including on social media (Frenkel, Alba, & Zhong, 2020; Russonello, 2020).

In the case of COVID-19, this misinformation comes in many forms – from conspiracy theories about the virus being created as a biological weapon in China to claims that coconut oil kills the virus. At its worst, misinformation of this sort may cause people to turn to ineffective (and potentially harmful) remedies, as well as to either overreact (e.g., by hoarding goods) or, more dangerously, underreact (e.g., by deliberately engaging in risky behavior and inadvertently spreading the virus). As a consequence, it is important to understand why people believe and share false (and true) information related to COVID-19 – and to develop interventions to increase the quality of information that people share online.

Here we apply a cognitive science lens to [the problem of COVID-19 misinformation]. In particular, we test whether previous findings from the domain of political "fake news" (fabricated news stories presented as if from legitimate sources; Lazer et al., 2018) extend to misinformation related to COVID-19. We do so by drawing on a recently proposed attention-based account of misinformation sharing on social media (Pennycook, Epstein, et al., 2020). By this account, people generally wish to avoid spreading misinformation and, in fact, are often able to tell truth from falsehood; however, they nonetheless share false and misleading content because the social media context focuses their attention on factors other than accuracy (e.g., partisan alignment). As a result, users get distracted from even *considering* accuracy when deciding whether to share – leading them to not implement their preference for accuracy and instead share misleading content. In support of this attention-based argument, Pennycook, Epstein, et al., (2020) found that most participants were surprisingly good at discerning between true and false political news when asked to assess the headlines' accuracy – yet headline veracity had very little impact on participants' willingness to share the headlines on social media. Accordingly, subtle nudges that made the concept of accuracy salient increased the veracity of subsequently shared political content – both in survey experiments and a large field experiment on Twitter.

It is unclear, however, how (or whether) these results will generalize to COVID-19. First, it may be that a greater level of specialized knowledge is required to correctly judge the accuracy of health information relative to political information. Thus, participants may be unable to discern true from false in the context of COVID-19, even when they do consider accuracy. Second, it is unclear whether participants will be distracted from accuracy in the way that Pennycook, Epstein, et al., (2020) observed for political headlines. A great deal of evidence suggests that people are motivated to seek out, believe, and share politically congenial information (Kahan, Peters, Dawson, & Slovic, 2017; Kunda, 1990; Lee, Shin, & Hong, 2018; Mercier & Sperber, 2011; Shin & Thorson, 2017). Thus, it seems likely that these partisan motivations are what is distracting participants from accuracy in Pennycook, Epstein, et al., (2020), who used highly political stimuli. If so, we would *not* expect similar results for COVID-19. Much of the COVID-19 (mis)information circulating online is apolitical (e.g., that COVID-19 can be cured by Vitamin-C). Furthermore, despite some outliers, there is relatively little partisan disagreement regarding the seriousness of the pandemic (Galston, 2020). Indeed, as described below, there were no partisan differences in likelihood to believe true or false COVID-19 headlines in our data. Thus, if partisanship was the key distractor, people should not be distracted from accuracy when deciding whether to share COVID-19-related content. On the contrary, one might reasonably expect the life-and-death context of COVID-19 to particularly focus attention on accuracy.

In the current paper, we therefore investigate the role that inattention plays in the sharing of COVID-19-related content. Study 1 tests for a dissociation between accuracy judgments and sharing intentions when participants evaluate a set of true and false news headlines about COVID-19. Study 1 also tests for correlational evidence of inattention by evaluating the relationship between truth discernment and analytic cognitive style (as well as examining science knowledge, partisanship, geographic proximity to COVID-19 diagnoses, and the tendency to over- versus under-use medical services). Study 2 experimentally tests whether subtly making the concept of accuracy salient increases the quality of COVID-19 information that people are willing to share online.

Study 1

Methods

We report how we determined our sample size, all data exclusions, all manipulations, and all measures in the study. Our data, materials, and preregistration are available online (link). At the end of both surveys, we informed participants which of the headlines were accurate (by re-presenting the true headlines).

Participants

This study was run on March 12th, 2020. We recruited 1000 participants using Lucid, an online recruiting source that aggregates survey respondents from many respondent providers (Coppock & Mcclellan, 2019). Lucid uses quota sampling to provide a sample that is matched to the U.S. public on age, gender, ethnicity, and geographic region. We selected Lucid to provide a sample for this study because it provides a sample that is reasonably representative of the U.S. population while being affordable for large samples. Our sample sizes for both studies were based on the following factors: 1) 1000 is a large sample size, 2) it is a nice round number, 3) it was within our budget, and 4) it is similar to what is used in past research (Pennycook et al., 2020). In total, 1143 participants began the study. However, 192 did not indicate using Facebook or Twitter and therefore did not complete the survey. A further 98 participants did not finish the study and were removed. The final sample consisted of 853 participants (mean age = 46; age range = 18 to 90; 357 males, 482 females, and 14 other/prefer not to answer).

Materials and Procedure

News evaluation/sharing task. Through a partnership with Harvard Global Health Institute, we acquired a list of 15 false and 15 true news headlines relating to COVID-19 (available online: link). The false headlines were deemed to be false by authoritative sources such as fact-checking sites like snopes.com and factcheck.org, health experts such as mayoclinic.com, and credible science websites such as www.livescience.com. After the study was completed, we realized that one of the false headlines (about bats being the source of the virus) is more misleading or unverified than untrue – however, removing this headline did not change our results and so we retained it. The true headlines came from reliable mainstream media sources.

Headlines were presented in the format of Facebook posts: a picture accompanied by a headline and lede sentence. Participants were randomized into two conditions. In the Accuracy Condition, they were asked: "To the best of your knowledge, is the claim in the above headline accurate?" (yes/no). In the Sharing Condition, they were asked: "Would you consider sharing this story online (for example, through Facebook or Twitter?)" (yes/no); the validity of this self-report sharing measure is evidenced by the observation that news headlines which MTurkers report a higher likelihood of sharing do indeed receive more shares on Twitter (Mosleh, Pennycook, & Rand, 2020). We counterbalanced the order of the yes/no options (No/Yes vs. Yes/No) across participants. Headlines were presented in a random order.

A key outcome from the news task is truth *discernment* – i.e., the extent to which individuals distinguish between true and false content in their judgments (Pennycook & Rand, 2019b). Discernment is defined as the difference in accuracy judgments (or sharing intentions) between true and false headlines. For example, an individual who shared 9 out of 15 true headlines and 12 out of 15 false headlines would have a discernment level of 0.6 – 0.8 = -0.2; while an individual who shared 9 out of 15 true headlines and 3 out of 15 false headlines would have a discernment level of 0.6 – 0.2 = 0.4. Thus, a higher discernment score indicates a higher sensitivity to truth relative to falsity.

COVID-19 questions. Prior to the news evaluation task, participants were asked two questions specific to the COVID-19 pandemic. First, they were asked "How concerned are you about COVID-19 (the new coronavirus)?", which they answered using a sliding scale from 0 (not concerned at all) to 100 (extremely concerned). Second, they were asked "How often do you proactively check the news regarding COVID-19 (the new coronavirus)?", which they answered on a scale from 1 (never) to 5 (very often).

Additional correlates. We gave participants a 6-item Cognitive Reflection Test (CRT) (Frederick, 2005) that consisted of a reworded version of the original 3-item test and 3 items from a non-numeric version (we excluded the "hole" item) (Thomson & Oppenheimer, 2016). The CRT is a measure of one's propensity to reflect on intuitions (Pennycook, Cheyne, Koehler, & Fugelsang, 2016; Toplak, West, & Stanovich, 2011) that has strong test-retest reliability (Stagnaro, Pennycook, & Rand, 2018). All of the CRT items are constructed to elicit an intuitive but incorrect response. Consider, for example, the following problem: If you are running a race and pass the person in second place, what place are you in? For many people, the intuitive response of "first place" pops into mind – however, this is incorrect (if you pass the person in second place, you overtake their position and are now in second place yourself). Thus, correctly answering CRT problems is associated with reflective thinking. The CRT had acceptable reliability in Study 1 (Cronbach's α = .69).

Participants also completed a general science knowledge quiz – as a measure of general background knowledge for scientific issues – that consisted of 17 questions about basic science facts (e.g., "Antibiotics kill viruses as well as bacteria", "Lasers work by focusing sound waves") (McPhetres & Pennycook, 2020). The scale had acceptable reliability (Cronbach's α = .77).

We also administered the Medical Maximizing-Minimizing Scale (Scherer et al., 2016), which measures the extent to which people are either "medical maximizers" who tend to seek health care even if for minor issues or, rather, "medical minimizers" who tend to avoid health care unless absolutely necessary. The MMS scale also had acceptable reliability (Cronbach's α = .86).

Finally, in addition to various demographic questions, we measured political ideology on both social and fiscal issues, in addition to Democrat v. Republican party alignment.

Attention checks. Following the recommendations of Berinsky, Margolis, and Sances (2014), we added three screener questions that put a subtle instruction in the middle of a block of text. For example, in a block of text ostensibly about which news sources people prefer, we asked participants to select two specific options ("FoxNews.com and NBC.com") if they were reading the text. Full text for the screener questions is available online (along with the full materials for the study; link). Screeners were placed just prior to the news evaluation/sharing task, after the CRT, and after the science knowledge and MMS scales. To maintain the representativeness of our sample, our main analyses follow our pre-registered plan to include all participants, regardless of attentiveness. As a robustness check, we show in the Supplementary Information (SI) Table S2 that our key result is robust (the effect size for the interaction between content type and condition remained consistent) across levels of attentiveness.

Analysis

All analyses of headline ratings are conducted at the level of the rating, using linear regression with robust standard errors clustered on participants and headline.[1] Ratings are z-scored, all individual difference measures are z-scored, and experimentally manipulated variables (headline veracity and condition) are coded as -0.5 and 0.5. Our main analyses use linear probability models instead of logistic regression because the coefficients are more readily interpretable. However, logistic regression yielded qualitatively equivalent results. The coefficient on headline veracity indicates overall level of discernment (the difference between responses to true versus false headlines), and the interaction between condition and headline veracity indicates the extent to which discernment differs between the experimental conditions.

Results

Accuracy versus sharing

We begin by comparing discernment – the difference between responses to true versus false headlines – across conditions. As predicted, we observe a significant interaction between headline veracity and condition, β=-0.126, $F(1,25586)=42.24$, $p<.0001$, such that discernment was higher for accuracy judgments than sharing intentions (Figure 1; similar results are obtained when excluding the few headlines that did not contain clear claims of fact, or that were political in nature, see SI Table S3). In other words, veracity had a much bigger impact on accuracy judgments, Cohen's d=0.657 [0.477, 0.836], $F(1,25586)=42.24$, $p<.0001$, than sharing intentions, d=0.121 [0.030, 0.212], $F(1,25586)= 6.74$, $p=.009$. In particular, for false headlines, 32.4% more people were willing to share the headlines than rated them as accurate. In Study 2, we build on this observation to test the impact of experimentally inducing participants to think about accuracy when making sharing decisions.

[1] Our preregistration erroneously indicated that we would cluster standard errors only on participant; doing so does not qualitatively change the results.

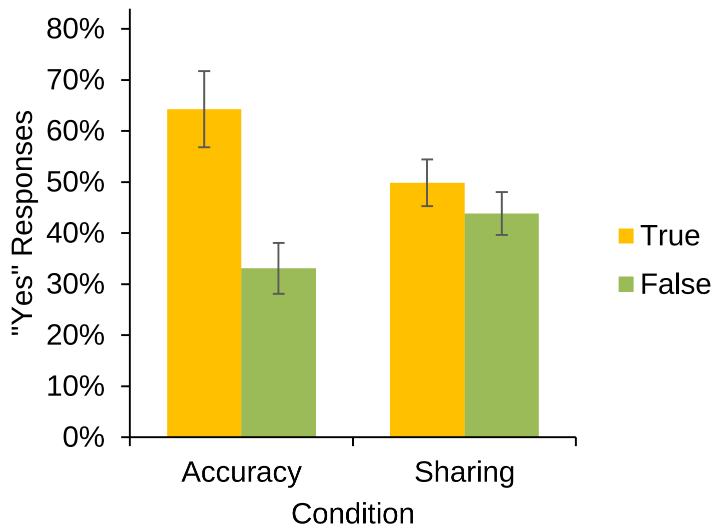

Figure 1. *Percentage of "yes" responses by headline veracity (true vs false) and condition (accuracy = "To the best of your knowledge, is the claim in the above headline accurate?"; sharing = "Would you consider sharing this story online (for example, through Facebook or Twitter)?"). Error bars indicate 95% confidence intervals.*

Individual differences and truth discernment

Before turning to Study 2, we examine how various individual difference measures correlate with discernment (i.e., how individual differences interact with headline veracity). All relationships reported below are robust to including controls for age, gender, education (college degree or higher versus less than a college degree), and ethnicity (white versus non-white) and all interactions between controls, veracity, and condition.

Cognitive Reflection. We find that CRT was positively related to both accuracy discernment (interaction between CRT and veracity, $F(1,25582)=34.95$, $p<.0001$, and sharing discernment (interaction between CRT and veracity, $F(1,25582)=4.98$, $p=.026$, but much more so for accuracy (3-way interaction between CRT, veracity, and condition; $F(1,25582)=14.68$, $p=.0001$). In particular, CRT was negatively correlated with belief in false headlines and uncorrelated with belief in true headlines, whereas CRT was negatively correlated with sharing of *both* types of headlines (albeit more negatively with sharing of false headlines compared to true headlines; for effect sizes, see Table 1). The pattern of CRT correlations observed here for COVID-19 misinformation is therefore consistent with what has been seen previously with political headlines (Pennycook & Rand, 2019b).

Table 1. *Standardized regression coefficients (β) for simple effects of each individual difference measure within each combination of condition and headline veracity. Values in parentheses show the results when including controls for age, gender, education (college degree or higher versus below), and ethnicity (white versus non-white) and all interactions between controls, veracity, and condition. †p<0.1, *p<0.05, **p<0.01, ***p<0.001.*

Condition:	**Accuracy**		**Sharing**	
Headline Veracity:	**False**	**True**	**False**	**True**
Cognitive Reflection Test	-0.148*** (-0.127***)	0.008 (0.006)	-0.177*** (-0.174***)	-0.134*** (-0.125***)
Science Knowledge	-0.080** (-0.067*)	0.079** (0.080**)	-0.082* (-0.030*)	-0.011 (-0.007)
Preference for Republican Party	0.003 (0.030)	-0.016 (-0.018)	-0.070* (-0.012)	-0.128*** (-0.079*)
Distance to closest disease epicenter	-0.046† (-0.005)	-0.021 (-0.028)	-0.099** (-0.091**)	-0.099** (-.078*)
Medical Maximizer-Minimizer Scale	0.130*** (0.120***)	0.047* (0.051*)	0.236*** (0.0207***)	0.233*** (0.200***)

Science knowledge. Like CRT, science knowledge was positively correlated with both accuracy discernment, $F(1,25552)=32.80$, $p<.0001$, and sharing discernment, $F(1,25552)=10.02$, $p=.002$, but much more so for accuracy (3-way interaction between science knowledge, veracity, and condition: $F(1,25552)=7.59$, $p=.006$). In particular, science knowledge was negatively correlated with belief in false headlines and positively with belief in true headlines; whereas science knowledge was negatively correlated with sharing of false headlines and uncorrelated with sharing of true headlines (for effect sizes, see Table 1).

Exploratory measures. Distance from the nearest COVID-19 epicenter (defined as a county with at least 10 confirmed coronavirus cases when the study was run; log-transformed because of right-skew) was not significantly related to belief in either true or false headlines, but was negatively correlated with sharing intentions for both true and false headlines (no significant interactions with veracity, $p>0.2$; interaction between distance and condition was marginal, $F(1, 25522)=3.07$, $p=0.080$). The medical maximizer-minimizer scale was negatively correlated with accuracy discernment, $F(1,25582)=11.26$, $p=.0008$, such that medical maximizers show greater belief in both true and false headlines (this pattern is more strongly positive for belief in false headlines); in contrast, there was no such correlation with sharing discernment, $F(1,25582)=0.03$, $p=.87$. Thus, medical maximizers are more likely to consider sharing *both* true and false headlines to the same degree (the 3-way interaction between maximizer-minimizer, veracity, and condition was significant; $F(1,25582)=7.58$, $p=.006$). Preference for the Republican party over the Democratic party (partisanship) was not significantly related to accuracy discernment, $F(1,25402)=0.45$, $p=.50$, but was significantly negatively related to sharing discernment, $F(1,25402)=8.28$, $p=.004$, such that stronger Republicans were *less* likely to share both true and false headlines, but were particularly less likely (relative to Democrats) to share true headlines (however, the 3-way interaction between partisanship, veracity, and condition was not significant, $F(1,25402)=1.62$, $p=.20$). For effect sizes, see Table 1.

Individual differences and COVID-19 attitudes

Finally, in Table 2 we report how all of the above variables relate to concern about COVID-19 and how often people proactively check COVID-19 related news (self-reported). Both measures are negatively correlated with CRT score and preference for the Republican party over the Democratic Party; positively correlated with being a medical maximizer; and unrelated to science knowledge when using pairwise correlations, but significant positively related to science knowledge in models with all covariates plus demographic controls. Distance to the nearest county with at least 50 COVID-19 diagnoses was uncorrelated with concern, and negatively correlated with news-checking (although uncorrelated with news checking in the model with all measures and controls).

Table 2. *Pairwise correlations among concern about COVID-19, proactively checking news about COVID-19, and the individual difference measures. *p<0.05, **p<0.01, ***p<0.001. Values in parentheses show standardized coefficients from linear regression models including all individual difference measures as well as age, gender, education (college degree or higher versus below), and ethnicity (white versus non-white).*

	COVID-19 Concern	COVID-19 News-Checking	CRT	Science Knowledge	Partisanship (Republican)	Distance to epicenter	Medical Maximizing
COVID-19 Concern	-						
COVID-19 News-Checking	.64***	-					
Cognitive Reflection Test (CRT)	-.22*** (-.17***)	-.10* (-.07*)	-				
Science Knowledge	-.001 (.10**)	.06 (.10**)	.40***	-			
Partisanship (Republican)	-.27*** (-.19***)	-.21*** (-.15***)	.09**	-.08*	-		
Distance to epicenter	-.05 (-.02)	-.07* (-.04)	.01	-.03	.10*	-	
Medical Maximizing	.41*** (.36***)	.36*** (.34***)	-.23***	-.16***	-.15***	-.05	-

Study 2

Methods

Participants

This study was run on March 13-15th, 2020. We recruited 1000 participants using Lucid. In total, 1145 participants began the study. However, 177 did not indicate using Facebook or Twitter and therefore did not complete the survey. A further 112 participants did not complete the study. The final sample consisted of 856 participants (mean age = 47; age range = 18 to 86; 385 males, 468 females, and 8 other/prefer not to answer).

Materials and Procedure

Accuracy induction. Participants were randomized into one of two conditions. In the Control Condition, they began the news sharing task as in Study 1. In the Treatment Condition, they rated the accuracy of a single headline (unrelated to COVID-19) at the beginning of the survey; as in Pennycook, Epstein, et al. (2020), this was framed as being for a pretest. Participants saw one of four possible headlines, all politically neutral and unrelated to COVID-19 (see link for materials). An advantage of this design is that the manipulation is subtle and not explicitly linked to the main task. Thus, it is unlikely that any *between-condition* difference is driven by participants believing that the accuracy question at the beginning of the treatment condition was designed to make them take accuracy into account when making sharing decisions during the main experiment. It is therefore relatively unlikely that any treatment effect would be due demand characteristics or social desirability.

News sharing task. Participants were presented the same headlines as for Study 1 and (as in the sharing condition of Study 1) were asked about their willingness to share the headlines on social media. In this case, however, we asked: “If you were to see the above on social media, how likely would you be to share it?”, which they answered on a 6-point scale from 1 (extremely unlikely) to 6 (extremely likely). As described above, some evidence in support of the validity of this self-report sharing intentions measure comes from Mosleh, Pennycook, & Rand (2020). Further support for the specific paradigm used in this experiment – where participants are asked to rate the accuracy of a headline and then go on to indicate sharing intentions – comes from Pennycook, Epstein, et al. (2020), who find similar results using this paradigm on Mturk and in a field experiment on Twitter measuring actual (rather than hypothetical) sharing.

Other measures. All of the additional measures included in Study 1 were also included for Study 2.

Attention checks. The same screeners included in Study 1 were also included in Study 2. As in Study 1, to maintain the sample’s representativeness we present the results for all subjects in the main text, and show the robustness of our key result across levels of attentiveness in SI Table S5.

Analysis.

All analyses of are conducted at the level of the rating, using linear regression with robust standard errors clustered on participants and headline. Sharing intentions are rescaled such that 1 on the 6-point Likert scale is 0 and 6 on the 6-point Likert scale is 1.

Results

As predicted, we observe a significant positive interaction between headline veracity and treatment, β=0.039, $F(1,25623)=17.88$, $p<.0001$, such that the treatment increased sharing discernment (i.e., participants were more likely to share true headlines relative to false headlines after they rated the accuracy of a single non-COVID headline; Figure 2). Specifically, although participants in the control condition were not significantly more likely to say that they would share true headlines compared to false headlines, d=0.050 [-0.033, 0.133], $F(1,25623)=1.41$, $p=.24$, in the treatment condition sharing intentions for true headlines were significantly higher than for false headlines, d=0.142 [0.049, 0.235], $F(1,25623)=8.89$, $p=.003$. Quantitatively, sharing discernment (the difference in sharing likelihood of true relative to false headlines) was 2.8 times higher in the treatment condition compared to the control condition. Furthermore, the treatment effect on sharing discernment was not significantly moderated by CRT performance, science knowledge, partisanship, distance to nearest infection epicenter, or the medical maximizer-minimizer scale (p's >.10 for all 3-way interactions between headline veracity, treatment, and individual difference measure). The treatment effect was also robust to excluding the few headlines that did not contain clear claims of fact, or that were political in nature (see SI Table S6).

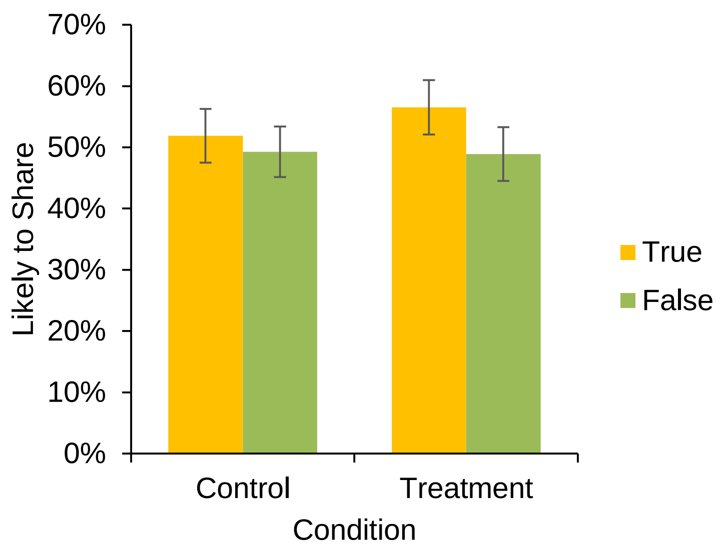

Figure 2. *Percentage of headlines participants said they would be likely to share by headline veracity (true vs false) and condition. For this visualization, we discretize sharing intentions using the scale midpoint (i.e. 1-3=0, 4-6=1) to give a more easily interpretable measurement; all analyses are conducted using the full (non-discretized) scale, and plotting the average (non-discretized) sharing intentions looks qualitatively similar. For the equivalent plot using mean sharing intentions instead of the discretized proportions, see SI Figure S1. Error bars indicate 95% confidence intervals.*

Our interpretation of the treatment effect is that the accuracy nudge makes participants more likely to consider accuracy when deciding whether to share. Based on this mechanism, the extent to which the treatment increases or decreases sharing of a given headline should reflect the underlying perceptions of the headline's accuracy. That is, increasing an individual's attention to accuracy should yield the largest changes in sharing intentions for headlines that are more unilaterally perceived to be true or false. To provide evidence for such a relationship, we perform an item-level analysis. For each headline, we examine how the effect of the treatment on sharing (i.e., average sharing intention in treatment minus average sharing intention in the control) varies based on the average accuracy rating given to that headline by participants in the Accuracy condition of Study 1. Because participants in Study 2 did not rate the accuracy of the COVID-19 related headlines, we use average Study 1 ratings as a proxy for how accurate participants in Study 2 would likely deem the headlines to be. As shown in Figure 3, there is indeed a strong positive correlation between a headline's perceived accuracy and the impact of the treatment, $r(28)=0.76$, $p<.0001$. Headlines that are more likely to be identified as true (based on Study 1 data) are more strongly positively impacted (sharing increases) by nudging people to consider accuracy. This suggests that the accuracy nudge is, as we hypothesized, increasing people's attention to whether the headlines seem true or not when they decide what to share.

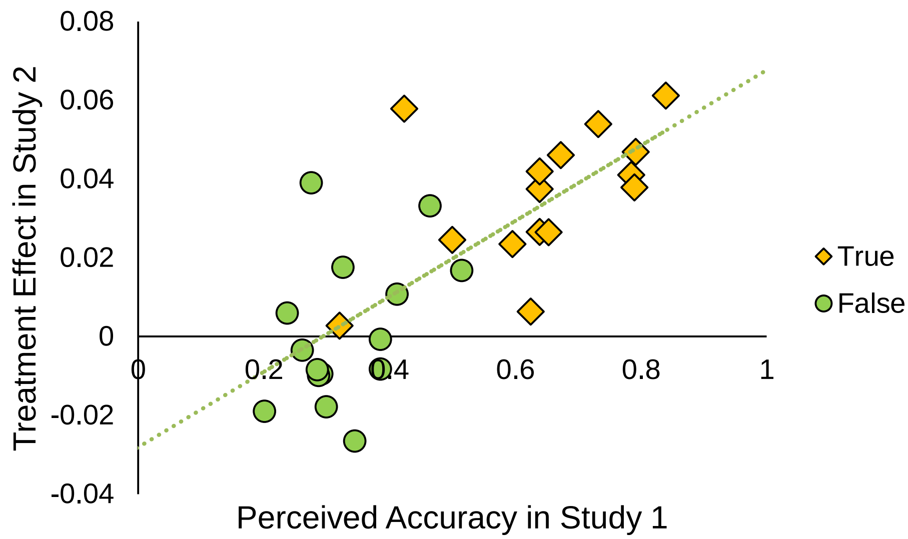

Figure 3. *Relationship across headlines between the effect of the treatment in Study 2 and the average accuracy rating from participants in the Accuracy condition of Study 1.*

Discussion

Our results are consistent with an attention-based account (Pennycook et al., 2020) of COVID-19 misinformation transmission on social media. In Study 1, participants were willing to share fake news about COVID-19 that they would have apparently been able to identify as being untrue if they were asked directly about accuracy. Put differently, participants were far less discerning if they were asked about whether they would share a headline on social media than if they were asked about its accuracy. Furthermore, individuals who were more likely to rely on their intuitions and who were lower in basic scientific knowledge were worse at discerning between true and false content (in terms of both accuracy and sharing decisions). In Study 2, we demonstrated the promise of a behavioral intervention informed by this attention-based account. Prior to deciding which headlines they would share on social media, participants were subtly primed to think about accuracy by being asked to rate the accuracy of a single news headline. This minimal, content-neutral intervention more than doubled participants' level of discernment between sharing true versus false headlines.

This research has important theoretical and practical implications. From a theoretical perspective, our findings shed new light on the theoretical perspective that inattention plays an important role in the sharing of misinformation online. By demonstrating the role of inattention in the context of COVID-19 misinformation (rather than politics), our results suggest that partisanship is *not*, apparently, the key factor distracting people from accuracy on social media. Instead, the tendency to be distracted from accuracy on social media seems more general. Thus, it seems likely that people are being distracted from accuracy by more fundamental aspects of the social media context. For example, social media platforms provide immediate, quantified feedback on the level of approval from one's social connections (e.g., "likes" on Facebook). Thus, attention may by default be focused on concerns about social validation and reinforcement (e.g., Brady, Crockett, & Van Bavel, 2020; Crockett, 2017), rather than accuracy. Another possibility is that, since news content is intermixed with content where accuracy is not relevant (e.g. baby photos, animal videos), people may habituate to a lower level of accuracy consideration when in the social media context. The finding that people seem to lack regard for accuracy even when making judgments about sharing content related to a global pandemic raises important questions about the nature of the social media ecosystem.

The present studies also add to the literature on reasoning and truth discernment. While much of the discussion around fake news has focused on political ideology and partisan identity (Beck, 2017; Kahan, 2017; Taub, 2017; Van Bavel & Pereira, 2018), our data are more consistent with recent studies on political misinformation that provide both correlational (Pennycook & Rand, 2019b) (including data from Twitter sharing; Mosleh, Pennycook, Arechar, & Rand, 2020) and experimental (Bago, Rand, & Pennycook, 2019) evidence for an important role of analytic cognitive style. That is, our data suggest that an important contributor to lack of truth discernment for health misinformation is the type of intuitive or emotional thinking that has been associated with conspiratorial beliefs (Swami, Voracek, Stieger, Tran, & Furnham, 2014; Vitriol & Marsh, 2018) and superstition (Elk, 2013; Lindeman & Svedholm, 2012; Risen, 2015). These findings highlight the importance of reflecting on incorrect intuitions and avoiding the traps of cognitive miserliness, regardless of political ideology, for a variety of psychological outcomes (Pennycook, Fugelsang, & Koehler, 2015; Stanovich, 2005).

From a practical perspective, misinformation is a particularly significant problem in uncertain news environments (e.g., immediately following a major news event; Starbird, 2019; Starbird, Maddock, Orand, Achterman, & Mason, 2014). In cases where having high quality information may literally be a matter of life-and-death – such as for COVID-19 – the impetus to develop interventions to fight misinformation become even more dire. Consistent with recent work on political misinformation (Fazio, 2020; Pennycook et al., 2020), here we find that simple and subtle reminders about the concept of accuracy may be sufficient to improve people's sharing decisions regarding information about COVID-19, and therefore improve the accuracy of the information about COVID-19 on social media. Although accuracy nudges are far from a complete solution, the intervention may nonetheless have important downstream effects on the overall quality of information shared online (e.g., due to network effects; see Pennycook, Epstein, et al., 2020). Furthermore, our treatment translates directly into a real-world intervention that social media companies could easily deploy by periodically asking users to rate the accuracy of randomly sampled headlines. Such ratings could also potentially help identify misinformation via crowdsourcing (Pennycook & Rand, 2019a) – especially given that, at least for the 30 headlines considered here, participants (on average) rated the true headlines as much more accurate than the false headlines.

Our research has several limitations. Perhaps most importantly, our evidence is restricted to the United States and therefore needs to be tested elsewhere in the world. Next, although our sample was quota-matched to the U.S. population on age, gender, ethnicity, and region, it was not obtained via probability sampling and therefore should not be considered nationally representative. We also used a particular set of true and false headlines about COVID-19. It is important for future work to test the generalizability of our findings to other headlines, and to (mis)information about COVID-19 that comes in forms other than headlines (e.g., emails/text posts/memes about supposed disease cures). Finally, our sharing intentions were hypothetical and our experimental accuracy induction was performed in a "lab" context. Thus, one may be concerned about whether our results will extend to naturalistic social media contexts. We see three reasons to expect that our results will generalize to real sharing behavior. First, there is evidence (at the level of the headline) that self-report sharing intentions correlate meaningfully with actual sharing on platform (Mosleh, Pennycook, & Rand, 2020). Second, because our manipulation was quite subtle, we believe it is unlikely that differences in sharing intentions between the treatment and control (as opposed to overall sharing levels) are driven by demand effects or social desirability bias. Third, past research using similar methods has shown evidence of external validity: Pennycook, Epstein, et al. (2020) targeted the same accuracy reminder intervention at political misinformation and found that the results from the survey experiments replicated when they delivered the intervention via direct message on Twitter, significantly improving the quality of subsequent tweets from individuals who are prone to sharing misleading political news content.

Conclusion

Our results shed light on why people believe and share misinformation related to COVID-19 and point to a suite of interventions based on accuracy nudges that social media platforms could directly implement. Such interventions are easily scalable and do not require platforms to make decision about what content to censor. We hope that social media platforms will consider this approach in their efforts to improve the quality of information shared online.

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Competing interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

References

Bago, B., Rand, D. G., & Pennycook, G. (2019). Fake news, fast and slow: Deliberation reduces belief in false (but not true) news headlines. *Journal of Experimental Psychology: General*. https://doi.org/10.31234/OSF.IO/29B4J

Beck, J. (2017). This article won't change your mind: The fact on why facts alone can't fight false beliefs. *The Atlantic*. Retrieved from https://www.theatlantic.com/science/archive/2017/03/this-article-wont-change-your-mind/519093/

Berinsky, A. J., Margolis, M. F., & Sances, M. W. (2014). Separating the shirkers from the workers? Making sure respondents pay attention on self-administered surveys. *American Journal of Political Science*, *58*(3), 739–753. https://doi.org/10.1111/ajps.12081

Brady, W. J., Crockett, M. J., & Van Bavel, J. J. (2020). The MAD Model of Moral Contagion: The role of motivation, attention and design in the spread of moralized content online. *Perspectives on Psychological Science*. Retrieved from https://doi.org/10.31234/osf.io/pz9g6

Coppock, A., & Mcclellan, O. A. (2019). Validating the Demographic, Political, Psychological, and Experimental Results Obtained from a New Source of Online Survey Respondents. *Research & Politics*. Retrieved from https://alexandercoppock.com/papers/CM_lucid.pdf

Crockett, M. J. (2017). Moral outrage in the digital age. *Nature Human Behaviour*, *1*(11), 769–771. https://doi.org/10.1038/s41562-017-0213-3

Elk, M. van. (2013). Paranormal believers are more prone to illusory agency detection than skeptics. *Consciousness and Cognition*, *22*(3), 1041–1046. https://doi.org/10.1016/j.concog.2013.07.004

Fazio, L. (2020). Pausing to consider why a headline is true or false can help reduce the sharing of false news. *Harvard Kennedy School Misinformation Review*, *1*(2).

https://doi.org/10.37016/mr-2020-009

Frederick, S. (2005). Cognitive Reflection and Decision Making. *Journal of Economic Perspectives*, *19*(4), 25–42. https://doi.org/10.1257/089533005775196732

Frenkel, S., Alba, D., & Zhong, R. (2020, March 8). Surge of Virus Misinformation Stumps Facebook and Twitter. *The New York Times*. Retrieved from https://www.nytimes.com/2020/03/08/technology/coronavirus-misinformation-social-media.html

Galston, W. A. (2020, March 30). Polling shows Americans see COVID-19 as a crisis, don't think US is overreacting. Retrieved May 21, 2020, from https://www.brookings.edu/blog/fixgov/2020/03/30/polling-shows-americans-see-covid-19-as-a-crisis-dont-think-u-s-is-overreacting/

Kahan, D. M. (2017). Misconceptions, Misinformation, and the Logic of Identity-Protective Cognition. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2973067

Kahan, D., Peters, E., Dawson, E., & Slovic, P. (2017). Motivated numeracy and enlightened self-government. *Behavioural Public Policy*, *1*(1), 54–86.

Kunda, Z. (1990). The case for motivated reasoning. *Psychological Bulletin*, *108*(3), 480–498. https://doi.org/10.1037/0033-2909.108.3.480

Lazer, D., Baum, M. A., Benkler, Y., Berinsky, A. J., Greenhill, K. M., Menczer, F., … Zittrain, J. L. (2018). The science of fake news. *Science*, *9*(6380), 1094–1096. https://doi.org/10.1126/science.aao2998

Lee, C., Shin, J., & Hong, A. (2018). Does social media use really make people politically polarized? Direct and indirect effects of social media use on political polarization in South Korea. *Telematics and Informatics*, *35*(1), 245–254. https://doi.org/10.1016/j.tele.2017.11.005

Lindeman, M., & Svedholm, A. M. (2012). What's in a term? Paranormal, superstitious, magical and supernatural beliefs by any other name would mean the same. *Review of General Psychology*, *16*(3), 241–255. https://doi.org/10.1037/a0027158

McPhetres, J., & Pennycook, G. (2020). Science beliefs, political ideology, and cognitive sophistication. *PsyArXiv Working Paper*, 1–33. https://doi.org/10.31219/OSF.IO/AD9V7

Mercier, H., & Sperber, D. (2011). Why do humans reason? Arguments for an argumentative theory. *Behavioral and Brain Sciences*, *34*(2), 57–74. https://doi.org/10.1017/S0140525X10000968

Mosleh, M., Pennycook, G., Arechar, A. A., & Rand, D. (2020). Digital Fingerprints of Cognitive Reflection. *PsyArXiv Working Paper*, 1–20. https://doi.org/10.31234/OSF.IO/QASWN

Mosleh, M., Pennycook, G., & Rand, D. (2020). Self-reported willingness to share political news articles in online surveys correlates with actual sharing on Twitter. *PLOS One*, *15*, e0228882. https://doi.org/10.1371/journal. pone.0228882

Pennycook, G., Cheyne, J. A., Koehler, D. J., & Fugelsang, J. A. (2016). Is the cognitive reflection test a measure of both reflection and intuition? *Behavior Research Methods*, *48*, 341–348. https://doi.org/10.3758/s13428-015-0576-1

Pennycook, G., Epstein, Z., Mosleh, M., Arechar, A. A., Eckles, D., & Rand, D. (2020). Understanding and reducing the spread of misinformation online. *PsyArXiv Working Paper*, 1–63. https://doi.org/10.31234/OSF.IO/3N9U8

Pennycook, G., Fugelsang, J. A., & Koehler, D. J. (2015). Everyday Consequences of Analytic Thinking. *Current Directions in Psychological Science*, *24*(6), 425–432.

https://doi.org/10.1177/0963721415604610
Pennycook, G., & Rand, D. G. (2019a). Fighting misinformation on social media using crowdsourced judgments of news source quality. *Proceedings of the National Academy of Sciences*. https://doi.org/10.1073/pnas.1806781116
Pennycook, G., & Rand, D. G. (2019b). Lazy, not biased: Susceptibility to partisan fake news is better explained by lack of reasoning than by motivated reasoning. *Cognition*, *188*, 39–50. https://doi.org/10.1016/j.cognition.2018.06.011
Risen, J. L. (2015). Believing What We Do Not Believe: Acquiescence to Superstitious Beliefs and Other Powerful Intuitions. *Psychological Review*, No Pagination Specified. https://doi.org/10.1037/rev0000017
Russonello, G. (2020, March 13). Afraid of Coronavirus? That Might Say Something About Your Politics. *The New York Times*. Retrieved from https://www.nytimes.com/2020/03/13/us/politics/coronavirus-trump-polling.html
Scherer, L. D., Caverly, T. J., Burke, J., Zikmund-Fisher, B. J., Kullgren, J. T., Steinley, D., … Fagerlin, A. (2016). Development of the medical maximizer-minimizer scale. *Health Psychology*, *35*(11), 1276–1287. https://doi.org/10.1037/hea0000417
Shin, J., & Thorson, K. (2017). Partisan Selective Sharing: The Biased Diffusion of Fact-Checking Messages on Social Media. *Journal of Communication*, *67*(2), 233–255. https://doi.org/10.1111/jcom.12284
Stagnaro, M. N., Pennycook, G., & Rand, D. G. (2018). Performance on the Cognitive Reflection Test is stable across time. *Judgment and Decision Making*, *13*, 260–267.
Stanovich, K. E. (2005). *The robot's rebellion: Finding meaning in the age of Darwin*. Chicago, IL: Chicago University Press.
Starbird, K. (2019, July 25). Disinformation's spread: bots, trolls and all of us. *Nature*. Nature Publishing Group. https://doi.org/10.1038/d41586-019-02235-x
Starbird, K., Maddock, J., Orand, M., Achterman, P., & Mason, R. M. (2014). Rumors, False Flags, and Digital Vigilantes: Misinformation on Twitter after the 2013 Boston Marathon Bombing. In *iConference 2014 Proceedings* (pp. 654–662). iSchools. https://doi.org/10.9776/14308
Swami, V., Voracek, M., Stieger, S., Tran, U. S., & Furnham, A. (2014). Analytic thinking reduces belief in conspiracy theories. *Cognition*, *133*(3), 572–585. https://doi.org/10.1016/j.cognition.2014.08.006
Taub, A. (2017). The Real Story About Fake News Is Partisanship. *The New York Times*. Retrieved from https://www.nytimes.com/2017/01/11/upshot/the-real-story-about-fake-news-is-partisanship.html
Thomson, K. S., & Oppenheimer, D. M. (2016). Investigating an alternate form of the cognitive reflection test. *Judgment and Decision Making*, *11*(1), 99–113.
Toplak, M. E., West, R. F., & Stanovich, K. E. (2011). The Cognitive Reflection Test as a predictor of performance on heuristics-and-biases tasks. *Memory & Cognition*, *39*(7), 1275–1289. https://doi.org/10.3758/s13421-011-0104-1
Van Bavel, J. J., & Pereira, A. (2018). The partisan brain: An Identity-based model of political belief. *Trends in Cognitive Sciences*.
Vitriol, J. A., & Marsh, J. K. (2018). The illusion of explanatory depth and endorsement of conspiracy beliefs. *European Journal of Social Psychology*, *48*(7), 955–969. https://doi.org/10.1002/ejsp.2504

Supplementary Materials

Table S1. *Study 1 Item Analysis*

		All		Democrats		Republicans	
Headline	**Item Name**	**%Accurate**	**%Shared**	**%Accurate**	**%Shared**	**%Accurate**	**%Shared**
$425M in World Bank catastrophe bonds set to default	False-1	0.38	0.38	0.4	0.44	0.35	0.3
Is colloidal silver a cure for the coronavirus?	False-2	0.24	0.39	0.22	0.44	0.26	0.33
Coronavirus: North Korea's first confirmed patient shot dead	False-3	0.26	0.39	0.25	0.41	0.27	0.36
Coconut oil's history in destroying viruses, including coronaviruses	False-4	0.2	0.45	0.22	0.46	0.17	0.44
Governor Cuomo signs law using coronavirus as an excuse to take 'temporary' dictator powers	False-5	0.3	0.32	0.28	0.35	0.32	0.28
328 Chinese nationals caught entering US illegally	False-6	0.34	0.42	0.32	0.43	0.38	0.4
Vatican confirms Pope Francis and two aides test positive for coronavirus	False-7	0.28	0.44	0.27	0.49	0.27	0.38
Florida hospital reports a coronavirus infestation with multiple confirmed patients	False-8	0.46	0.48	0.5	0.49	0.42	0.47
Coronavirus in China: 23M quarantined, 2.8M infected, 112,000 dead	False-9	0.41	0.48	0.4	0.54	0.43	0.41
Vitamin C protects against Coronavirus	False-10	0.29	0.47	0.29	0.46	0.3	0.47
University of Tennessee scientists may have found cure	False-11	0.29	0.58	0.27	0.6	0.31	0.56
Unbelievable- Gates Foundation predicted 65 million death 3 months ago	False-12	0.39	0.48	0.38	0.53	0.39	0.42
FEMA proposes martial law to contain virus | New World Order	False-13	0.28	0.42	0.29	0.46	0.27	0.37
COVID-19 is now mutating into something indescribable	False-14	0.33	0.4	0.35	0.45	0.3	0.34

Experts think bats are the source of the Wuhan Coronavirus. At least 4 pandemics have originated in these animals	False-15	0.51	0.43	0.51	0.48	0.53	0.38
Spread of virus appears inevitable in US	True-1	0.79	0.55	0.81	0.64	0.76	0.43
Trump spent the past 2 years slashing the government agencies responsible for handling the coronavirus outbreak	True-2	0.42	0.46	0.54	0.58	0.27	0.31
Coronavirus infections increase in Italy	True-3	0.84	0.54	0.82	0.6	0.86	0.47
Why airport screening won't stop the spread of the coronavirus	True-4	0.64	0.49	0.67	0.53	0.6	0.44
Europe's outbreak worsens; Italy at forefront	True-5	0.78	0.53	0.78	0.6	0.8	0.45
Coronavirus: Many people in US will be exposed at some point	True-6	0.79	0.57	0.78	0.64	0.8	0.5
CDC: coronavirus spread may last into 2021; impact can be blunted	True-7	0.62	0.49	0.64	0.55	0.6	0.41
Israel declared 14-day quarantine for all arrivals	True-8	0.67	0.54	0.66	0.57	0.69	0.51
coronavirus poses tough challenge for economic policymakers	True-9	0.79	0.48	0.77	0.55	0.81	0.38
scientists warn nCoV more infectious than SARS, experts have doubts	True-10	0.6	0.41	0.6	0.47	0.6	0.33
Coronavirus: we need to start preparing for the next viral outbreak now	True-11	0.73	0.51	0.77	0.57	0.68	0.43
Amazon plans to prosecute sellers for price gouging during outbreak	True-12	0.64	0.61	0.63	0.64	0.65	0.58
Amid outbreak, Carnival Cruise Line offers on -ship credits to passengers who don't reschedule	True-13	0.65	0.46	0.65	0.46	0.65	0.45
Iran now has the highest coronavirus death toll outside of China, threatening wider middle east	True-14	0.5	0.48	0.48	0.54	0.52	0.41
Police in the US spread a false claim that meth is contaminated with virus	True-15	0.32	0.35	0.33	0.41	0.31	0.27

Table S2. *Study 1 main analysis for each attentiveness threshold. Unlike the main text analysis, here ratings (the dependent variable) are not z-scored so that outcome values are consistent across attentiveness levels.*

	(1) All Subjects	(2) ≥1 Screener Correct	(3) ≥2 Screener Correct	(4) All 3 Screeners Correct
Veracity (F=-0.5, T=0.5)	0.186***	0.195***	0.214***	0.269***
	(0.0289)	(0.0300)	(0.0318)	(0.0426)
Condition (Acc=-0.5, Sharing=0.5)	-0.0185	-0.0254	-0.0213	-0.0166
	(0.0261)	(0.0265)	(0.0283)	(0.0406)
Veracity X Condition	-0.252***	-0.266***	-0.297***	-0.325***
	(0.0387)	(0.0399)	(0.0421)	(0.0548)
Constant	0.478***	0.462***	0.441***	0.420***
	(0.0169)	(0.0174)	(0.0185)	(0.0260)
Observations	25,590	24,210	18,630	5,730
Subject clusters	853	807	621	191
Headline clusters	30	30	30	30
R-squared	0.050	0.056	0.067	0.101

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table S3. *Study 1 main analysis robustness checks when excluding various headlines. Model 2 excludes headlines False-2 (which was phrased a question), False-11 (which used hedged language and so was not strictly false), and Real-9 and Real-11 (which were opinion statements). Model 3 excludes headlines False-5, False-13, and True-2, which are explicitly political in nature. Model 4 excludes those three headlines plus False-12, True-1, True-9, True-11, and True-15, which are somewhat related to politics and policy. Models 5-7 excludes headlines based on the level of partisan disagreement observed in accuracy ratings from Study 1 (defined as the absolute value of the difference between average accuracy rating given by Democrats and average accuracy rating given by Republicans).*

	(1) All headlines	(2) Only claim of fact	(3) No political (narrow)	(4) No political (broad)	(5) Dem-Rep diff < 0.1	(6) Dem-Rep diff < 0.05	(7) Dem-Rep diff < 0.025
Veracity (F=-0.5, T=0.5)	0.372***	0.351***	0.374***	0.405***	0.391***	0.388***	0.399***
	(0.0578)	(0.0637)	(0.0583)	(0.0552)	(0.0576)	(0.0667)	(0.0606)
Condition (Acc=-0.5, Sharing=0.5)	-0.0370	-0.0357	-0.0449	-0.0493	-0.0498	-0.0433	-0.0468
	(0.0522)	(0.0521)	(0.0530)	(0.0539)	(0.0517)	(0.0560)	(0.0550)
Veracity X Condition	-0.504***	-0.431***	-0.539***	-0.554***	-0.529***	-0.522***	-0.460***
	(0.0775)	(0.0767)	(0.0795)	(0.0819)	(0.0761)	(0.0874)	(0.0841)
Constant	0.000369	-0.00646	0.0181	0.0273	0.00968	0.00748	0.0376
	(0.0338)	(0.0364)	(0.0340)	(0.0327)	(0.0337)	(0.0376)	(0.0351)
Observations	25,590	22,178	23,031	18,766	24,737	19,619	11,942
Subject clusters	853	853	853	853	853	853	853
Headline clusters	30	26	27	22	29	23	14
R-squared	0.050	0.042	0.053	0.059	0.055	0.054	0.051

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table S4. *Study 1 main analysis performed using multi-level model with maximal crossed random effects for subject and headline.*

```
Scaled residuals:
     Min       1Q   Median       3Q      Max
-2.98953 -0.65669 -0.02514  0.71164  2.81421

Random effects:
 Groups   Name        Variance Std.Dev. Corr
 Subject  (Intercept) 0.30109  0.5487
          Veracity    0.14390  0.3793   -0.12
 Headline (Intercept) 0.02438  0.1562
          Condition   0.04045  0.2011   -0.64
 Residual             0.58202  0.7629
Number of obs: 25590, groups:  id, 853; item_num, 30

Fixed effects:
                     Estimate   Std. Error      df    t value Pr(>|t|)
(Intercept)          0.000369   0.034477  56.314044   0.011    0.991
Veracity             0.372246   0.059253  30.904457   6.282    5.58e-07 ***
Condition           -0.037028   0.053401 106.157179  -0.693    0.490
Veracity:Condition  -0.503949   0.080200  34.928044  -6.284    3.30e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
             (Intr) Veracity Sharing
Veracity     -0.014
Condition    -0.371  0.000
Verac:Cond   0.000  -0.565   -0.027
```

Table S5. *Study 2 main analysis for each attentiveness threshold.*

	(1) All Subjects	(2) ≥1 Screener Correct	(3) ≥2 Screener Correct	(4) All 3 Screeners Correct
Veracity (F=0, T=1)	0.0191	0.0218	0.0288	0.0297
	(0.0161)	(0.0164)	(0.0185)	(0.0253)
Condition (Control=0, Treatment=1)	0.00139	0.000974	-0.00136	-0.0474
	(0.0202)	(0.0203)	(0.0230)	(0.0408)
Veracity X Condition	0.0343***	0.0330***	0.0390***	0.0320
	(0.00811)	(0.00848)	(0.0105)	(0.0190)
Constant	0.469***	0.463***	0.423***	0.440***
	(0.0177)	(0.0178)	(0.0200)	(0.0325)
Observations	25,627	24,727	18,497	6,176
Subject clusters	855	825	617	206
Headline clusters	30	30	30	30
R-squared	0.003	0.004	0.005	0.006

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

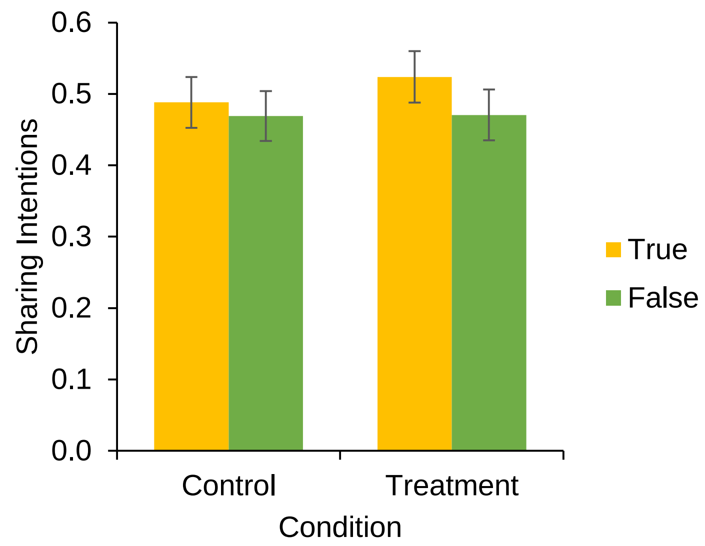

Figure S1. *Average sharing intentions by treatment in Study 2. The 6-point Likert scale used for sharing intentions is rescaled into the interval [0,1]. This figure complements Figure 2 in the main text, which instead shows the fraction of responses above the scale midpoint. Error bars indicate 95% confidence intervals.*

Table S6. *Study 2 main analysis robustness checks when excluding various headlines. Model 2 excludes headlines False-2 (which was phrased a question), False-11 (which used hedged language and so was not strictly false), and Real-9 and Real-11 (which were opinion statements). Model 3 excludes headlines False-5, False-13, and True-2, which are explicitly political in nature. Model 4 excludes those three headlines plus False-12, True-1, True-9, True-11, and True-15, which are somewhat related to politics and policy. Models 5-7 excludes headlines based on the level of partisan disagreement observed in accuracy ratings from Study 1 (defined as the absolute value of the difference between average accuracy rating given by Democrats and average accuracy rating given by Republicans).*

	(1) All headlines	(2) Only claim of fact	(3) No political (narrow)	(4) No political (broad)	(5) Dem-Rep diff < 0.1	(6) Dem-Rep diff < 0.05	(7) Dem-Rep diff < 0.025
Veracity (F=0, T=1)	0.0191	0.0236	0.0190	0.0244	0.0231	0.0224	0.0368
	(0.0161)	(0.0155)	(0.0163)	(0.0181)	(0.0162)	(0.0197)	(0.0225)
Condition (Control=0, Treatment=1)	0.00139	0.00189	0.00361	0.00396	0.00139	0.00140	0.00461
	(0.0202)	(0.0203)	(0.0202)	(0.0201)	(0.0202)	(0.0198)	(0.0201)
Veracity X Condition	0.0343***	0.0322***	0.0305***	0.0306***	0.0327***	0.0304***	0.0299***
	(0.00811)	(0.00773)	(0.00781)	(0.00765)	(0.00800)	(0.00701)	(0.00350)
Constant	0.469***	0.464***	0.473***	0.473***	0.469***	0.469***	0.469***
	(0.0177)	(0.0160)	(0.0179)	(0.0184)	-0.0177	(0.0198)	(0.0159)
Observations	25,627	22,208	23,065	18,794	24,772	19,646	11,962
Subject clusters	855	855	855	855	855	855	855
Headline clusters	30	26	27	22	29	23	14
R-squared	0.003	0.004	0.003	0.004	0.004	0.003	0.005

Table S7. *Study 2 main analysis performed using multi-level model with maximal crossed random effects for subject and headline.*

```
Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.9851 -0.5255 -0.0066  0.5422  4.0638

Random effects:
 Groups   Name        Variance  Std.Dev. Corr
 Subject  (Intercept) 0.0882607 0.297087
          Veracity    0.0165863 0.128788 -0.29
 Headline (Intercept) 0.0018571 0.043095
          Condition   0.0000858 0.009263 0.33
 Residual             0.0553302 0.235224
Number of obs: 25627, groups:  id, 855; item_num, 30

Fixed effects:
                  Estimate   Std. Error      df   t value Pr(>|t|)
(Intercept)       4.693e-01  1.842e-02 1.689e+02  25.483  < 2e-16 ***
Veracity          1.923e-02  1.743e-02 3.676e+01   1.103  0.27714
Condition         1.184e-03  2.088e-02 8.055e+02   0.057  0.95478
Vercity:Condition 3.430e-02  1.112e-02 1.690e+02   3.085  0.00238 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:
                 (Intr) Veracity Condition
Veracity        -0.495
Condition       -0.537  0.072
Veracity:Cond    0.128 -0.199   -0.326
```