The social media context interferes with truth discernment

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There is widespread concern about misinformation circulating on social media. In particular, many argue that the context of social media itself may make people susceptible to the influence of false claims. Here, we test that claim by asking whether simply considering sharing news on social media reduces people's ability to identify truth versus falsehood. In a large online experiment examining COVID-19 and political news (N=3,157 Americans), we find support for this possibility. When judging the accuracy of headlines, participants were worse at discerning truth from falsehood when they both evaluated accuracy and indicated their sharing intentions, compared to just evaluating accuracy. These results suggest people may be particularly vulnerable to believing false claims on social media, given that sharing is a core element of what makes social media "social."

Teaser

Simply considering whether to share news on social media reduces people's ability to tell truth from falsehood

Introduction

In recent years, the propagation of misinformation on social media has been a major focus of attention (*1–6*). Worries about "fake news", related to both politics and health (e.g. COVID-19), have led many to see social media as a threat to modern societies (and not, for example, as a tool for promoting collective intelligence and action). Common to such critiques is the assertion that people are more likely to fall for fake news on social media relative to other sources (*7–9*).

Central to this assertion is the idea that there are distinct affordances to the design of the social media context which may make people particularly susceptible to the influence of false claims (see (*7*) for a review). This idea is also captured by common assertions outside of the academic literature about the influence of social media algorithms on human psychology, such as in "The Social Dilemma" documentary where it is argued that the "technology that connects us also controls us" (*10*). Despite this major focus on the psychological impacts of social media, research investigating causal effects of social media on truth discernment are rather sparse.

Much of the discussion around this topic has focused on features of the social media platforms themselves that may promote misinformation. For example, it has been argued that social media environments often lack salient cues for the epistemic quality of content that exist in other contexts (*7*). Unlike traditional media, which naturally filters content for veracity with professional gatekeeping, social media is participatory and therefore allows mostly anyone to post (mostly) anything (*11, 12*). Furthermore, people often engage with news on social media in a manner that is fast-paced and distracted (quickly scrolling through a newsfeed that combines news and emotionally evocative non-news content), and prior work shows that time pressure and distraction (*13*), as well as emotional arousal (*14*) can impair one's ability to tell truth from falsehood. Social media also allows fringe groups to reach large and distributed communities, which in turn can create the illusion that the beliefs of these groups are widespread (*15*), as well as "false consensus" (*15, 16*).

Here, we consider an alternative, and in some sense more fundamental, way in which people may be particularly vulnerable to believing fake news on social media. We ask whether simply considering whether or not to share news online interferes with people's ability to tell true from false when judging the *accuracy* of news. There are a myriad of motivations for sharing news that go beyond just whether it is accurate (*17–20*). Because of this, simply making sharing decisions could lead people to be less discerning when asking to judge the news' accuracy.

There are two distinct (but not mutually exclusive) mechanisms by which asking about sharing could interfere with accuracy judgments. First, it may be that the act of choosing whether or not to share a specific piece of content affects how a social media user perceives the accuracy of that piece of content. In particular, choosing to share a piece of content may make you believe it more (or at least report that you believe it more). Reciprocally, choosing *not* to share a piece of content might make you believe it less (or at least report that you believe it less). Thus, this first account implies that people prefer to maintain consistency between sharing choices and accuracy judgments. An alternative mechanism is that thinking about whether to share content is *generally* distracting from the concept of accuracy by invoking a social media *mindset*. That is, simply asking about sharing may cause users to become more noisy when assessing accuracy because thinking about sharing causes people to be distracted by all of the non-accuracy related motivations and factors that are salient for the sharing choice (*17–20*). This second account therefore is built on the concept of spillover effects and implies that social media may have an effect because it involves a unique decision-making environment that (at least) fails to prioritize accuracy and truth.

To test whether deciding what to share interferes with users' accuracy judgments, and to disambiguate between these two potential mechanisms, we conducted an online experiment in which participants were shown a series of true and false headlines. We randomized participants to either (a) simply rate whether each headline is accurate (Accuracy-only condition), or (b) indicate whether they would share each headline on social media as well as rating its accuracy (and vary the question order, yielding the Sharing-Accuracy condition and the Accuracy-Sharing condition, see `(Fig. 1)`). This allowed us to test how participants' ability to identify the accuracy of true versus false headlines (accuracy discernment) changes when participants assess the headlines while also thinking about social media sharing. Finally, we also included a condition in which participants are only asked about sharing and not accuracy. This final Sharing-Only condition allowed us to assess the baseline shareability of each headline absent any accuracy prompt, and to test the replicability of past findings that asking about accuracy increases the quality of information people choose to share (*21*). Our data were collected across two experimental waves, one using text headlines about COVID-19 and a second using headline text + image pairs about politics. The waves also differed in the implementation of the Sharing condition: In the first wave, participants were just asked whether they would share each headline, whereas in the second wave participants were also asked whether they would like and comment on each headline. See Methods for details.

Results

We begin by assessing our key question of interest: How does accuracy discernment (the perceived accuracy of true relative to false headlines) change if participants also make sharing decisions `(Fig. 2)`? We fit a linear model predicting accuracy rating as a function of headline veracity (0=false, 1=true), experimental condition (encoded as per below), wave (z-

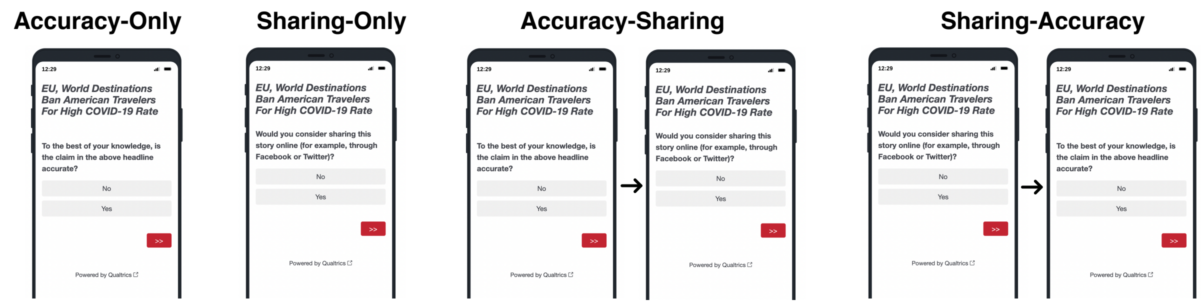

Figure 1: Visualization of different conditions. For the Accuracy-Sharing and Sharing-Accuracy conditions, participants saw the two questions on different pages.

scored dummy) and all interactions. We encode experimental condition using two variables: 1) sharing-asked, a dummy variable indicating whether the participant rated sharing as well as accuracy (sharing-asked, 0=Accuracy only, 1=Accuracy-Sharing or Sharing-Accuracy), which captures the effect of asking about sharing (collapsing across orders); and 2) order, a center-coded dummy indicating the order of the two ratings for conditions where both accuracy and sharing were asked (-0.5=Accuracy-Sharing, 0.5=Sharing-Accuracy, 0=Accuracy only), which allows us to test for order effects between the two sharing-asked conditions. Furthermore, because the wave dummy is z-scored, the coefficients on all lower-order interactions can be directly interpreted without needing to run a separate model excluding higher-order interactions with wave.

As predicted, the fitted model (full regression table shown in Table S1) shows a significant decrease in accuracy discernment when sharing is also asked (sharing-asked X veracity interaction, $b = -0.052$, $p < 0.001$). Contrary to our predictions, we find that the size of this effect is significantly larger when sharing is asked before accuracy (order X veracity interaction, $b = -0.037$, $p < 0.001$). However, we also observe a significant three way interaction between veracity, wave and sharing-asked ($p < 0.001$), such that the effect of asking about sharing on accuracy discernment varied across waves. Therefore, we consider the two waves separately.

Considering the first wave (COVID statements with no images or source information), we

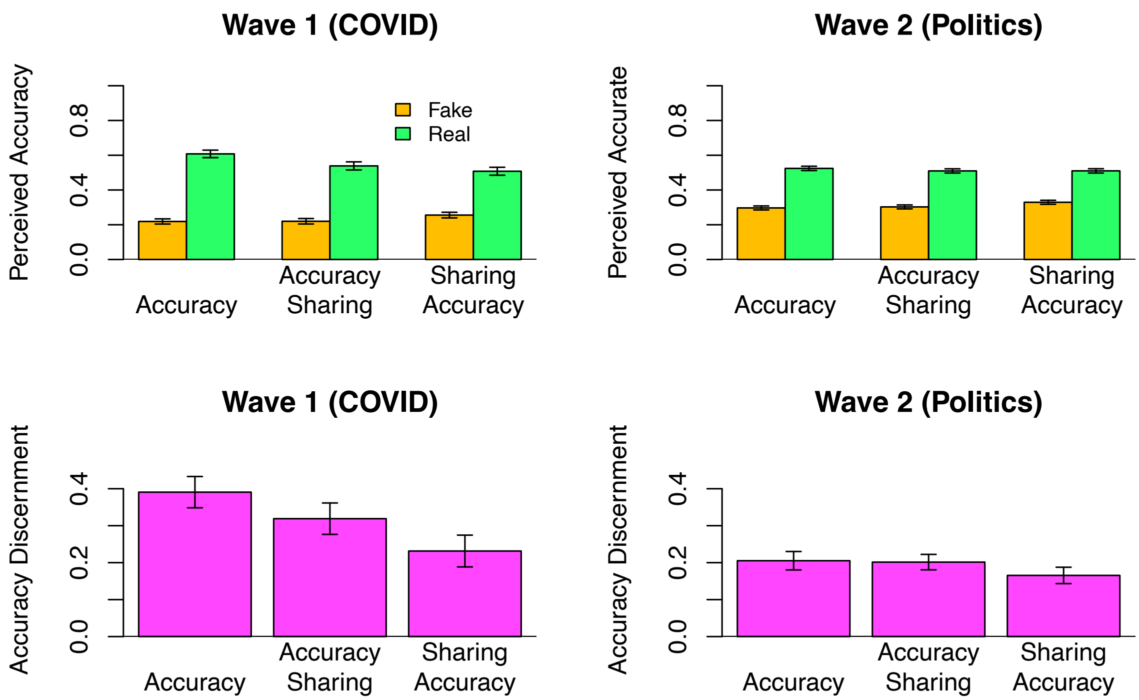

Figure 2: Top: Average perceived accuracy of true (green) and false (orange) news across waves and conditions. Error bars are 95% confidence intervals. Bottom: Subject level accuracy discernment (perceived accuracy of true minus perceived accuracy of false) across waves and conditions. Error bars are 95% confidence intervals.

find a significant main effect of asking about sharing, such accuracy discernment is significantly lower when sharing is also asked (sharing-asked X veracity interaction, $b = -0.103$ $p < 0.001$). However, we also find that the size of this effect was significantly different depending on whether accuracy or sharing was asked first (order X veracity interaction, $b = -0.066$, $p = 0.001$). Specifically, the decrease in accuracy discernment was substantially larger when sharing was asked before accuracy ($b = -0.136, p < 0.001$) compared to when accuracy was asked before sharing ($b = -0.070, p < 0.001$). To contextualize these effect sizes, asking about sharing before accuracy led to a 35% decrease in accuracy discernment compared to the Accuracy-Only baseline, and asking about sharing after accuracy led to a 18% decrease in accuracy discernment relative to the Accuracy-Only baseline. For full regression table, see SI Table S2.

Next we turn our attention to wave 2 (political headlines with image, source information, and liking/commenting as well as sharing in the Sharing conditions). Since wave 2 involved political headlines, we also include subject partisanship and political concordance in this model (as per our pre-registration). We once again find that, compared to the Accuracy-Only baseline, accuracy discernment is significantly lower when participants also indicate sharing intentions (sharing-asked X veracity interaction, $b = -0.035$ $p = 0.002$). We find that the size of this effect was marginally (but not significantly) different depending on whether accuracy or sharing was asked first (order X veracity interaction, $b = -0.021$, $p = 0.093$). That is, the decrease in accuracy discernment is somewhat larger when sharing is asked before accuracy ($b = -0.0455, p < 0.001$) compared to when accuracy is asked before sharing ($b = -0.0245, p = 0.058$). Thus, asking about sharing before accuracy led to a 28$\%$ decrease in sharing discernment compared to the Accuracy-Only baseline (and a non-significant 8$\%$ decrease for accuracy-then-sharing). We also find little evidence that these effects on accuracy discernment vary significantly based on headline concordance or subject partisanship (although we do find, consistent with past work (*22, 23*), that preference for the Republican party is associated with lower baseline accuracy discernment, $b = -0.032, p = 0.001$). For full regression table, see SI Table S3.

Overall, then, our data confirm the prediction that merely considering whether to share news on social media makes people worse at identifying the news' truth – particularly when people consider sharing prior to judging accuracy.

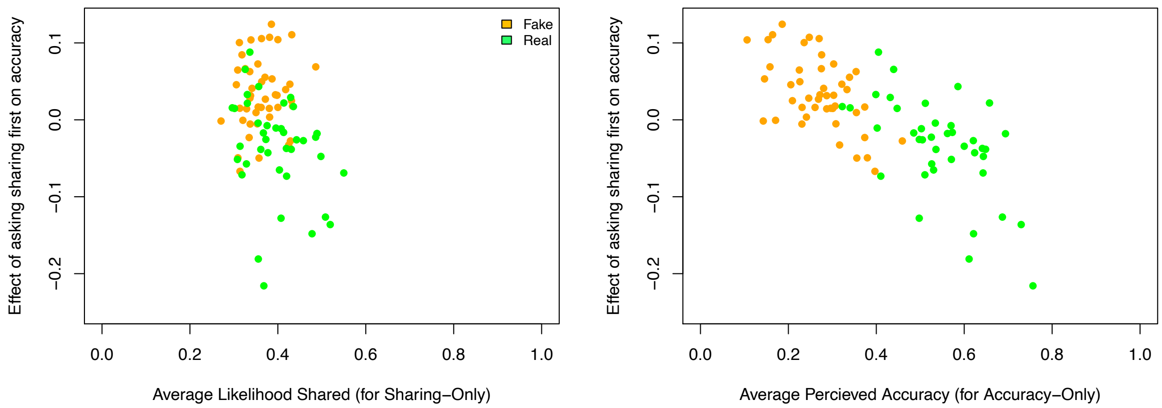

Figure 3: Item-level analysis comparing perceived accuracy in Accuracy-Only condition (left) and sharing likelihood in Sharing-Only condition (right) to the difference in perceived accuracy between the sharing-accuracy condition and the Accuracy-Only condition.

Headline-level analysis

We now aim to shed light on the mechanism underlying this effect. In particular, we seek to differentiate between the consistency-based and spillover-based accounts of why asking about sharing could interfere with accuracy discernment. We do so by evaluating each account's predictions about how the effect of asking about sharing should vary across headlines.

According to the consistency account, sharing a headline makes people think it is more accurate, and/or not sharing a headline makes people think it is less accurate. Thus, the consistency account predicts that, on average, asking about sharing should increase accuracy ratings for headlines people tend to share, and/or decrease accuracy ratings for headlines people tend not to share. In other words, the consistency account predicts a positive correlation between (i) how likely a headline is to be shared and (ii) how accuracy judgments of that headline change if sharing is also asked (i.e. perceived accuracy in Sharing-Accuracy minus perceived accuracy in Accuracy-Only).

According to the spillover account, asking about sharing should make people less sensitive to accuracy because they are distracted by the many other (non-accuracy-related) factors that are relevant to the choice of what to share. This is posited to be a general mindset effect, and thus should occur regardless of how likely the specific headline is to be shared. Instead, the effect of asking about sharing should depend on the baseline perceived accuracy of the headlines - if distraction just adds noise to accuracy ratings, we would expect asking about sharing to decrease the perceived accuracy of headlines that people would otherwise tend to believe and increase belief in headlines that people would otherwise tend to disbelieve. In other words, the spillover account predicts a negative correlation between (i) how accurate a headline is rated in the Accuracy-Only condition (baseline perceived accuracy) and (ii) how accuracy judgments of that headline change if sharing is also asked (i.e. perceived accuracy in Sharing-Accuracy minus perceived accuracy in Accuracy-Only).

In order to distinguish between these two mechanisms, we conduct two post-hoc headline-level analyses (`Fig. 3`)). A regression predicting the effect of asking about sharing on accuracy using independent variables of (a) sharing likelihood in Sharing-Only, (b) headline veracity, and (c) wave finds no significant effect of sharing likelihood in Sharing-Only ($p = 0.754$, see Table S6). This disconfirms the predictions of the consistency account. Conversely, a regression predicting the effect of asking about sharing on accuracy using independent variables of (a) perceived accuracy in Accuracy-Only, (b) headline veracity, and (c) wave finds a significant negative effect of perceived accuracy in Accuracy-Only ($p < 0.001$, see Table S7). This confirms the prediction of the spillover account.

Together, these headline-level analyses support the spillover account over the consistency account. It appears that having users consider whether or not to share headlines generally interferes with their judgments of headline accuracy, making those judgments noisier. This also explains why asking about sharing specifically reduces accuracy *discernment*: Because true headlines tend to be believed more than false headlines, asking about sharing reduces belief in true more than false.

Moderation by Partisanship

Next, we conduct an exploratory analysis assessing whether the effect of asking about sharing on accuracy discernment varies based on participant partisanship. In particular, we inspect the three-way interaction between news item veracity, treatment condition, and preference for the Republican versus Democratic parties (measured using a 1=Strong Democrat to 6 = Strong Republican Likert scale). The fitted model (shown in Table S8) shows a significant four way interaction between headline veracity, wave, sharing-asking, and partisanship ($b = 0.022$, $p = 0.029$). Therefore, we consider the two waves separately.

For wave 1 (COVID-19 headlines; regression table shown in Table S9), we observe significant moderation of the effect of asking about sharing by political partisanship, as measured by the 3-way interaction between veracity, sharing-asked, and partisanship ($b = -0.036, p = 0.047$). Specifically, asking about sharing leads to significantly more of a decrease in accuracy discernment for participants who more strongly favor the Republican party over the Democratic party. For wave 2 (political headlines; regression table shown in Table S10), conversely, we observe no significant interaction between participant partisanship, headline veracity, and the sharing-asked dummy ($b = 0.010$, $p = 0.358$).

The results are even stronger when we use a binary Democrat versus Republican partisanship measure (by splitting the 6 point partisanship Likert scale at the midpoint). Similarly to the continuous partisanship measure, we observe a significant four way interaction between headline veracity, wave, sharing-asking, and partisanship when using a binary measure of partisanship as well ($b = 0.026$, $p = 0.006$, see table S14) as well as significant moderation of the effect of asking about sharing by political partisanship for wave 1 ($b = -0.052, p = 0.004$) and no significant interaction between participant partisanship, headline veracity, and the sharing-asked dummy for wave 2 ($b = 0.007$, $p = 0.544$). See Figure 6).

Sharing Intentions

Finally, we turn our attention to the effect that asking about accuracy has on sharing intentions. The overall rates of sharing intentions (for both true and false) and discernment for both waves are shown in (Fig. 5). We fit a linear model predicting sharing intention as a function of headline veracity, experimental condition, wave and all interactions (coded as explained above in the perceived accuracy section). As shown in Table S4 in the Supplementary Information, we observe no significant interactions with wave, and therefore focus on the results pooling across waves.

Consistent with past work (*21*) – and oppositely from what we observed for the effect of asking about sharing on accuracy – we find that asking about accuracy *increases* sharing discernment ($b = 0.021, p = 0.017$). Importantly, the size of this effect does not significantly differ based on whether sharing or accuracy were asked first ($b = -0.001$, $p = 0.93$) - regardless of order, asking about accuracy translates into a roughly 53% increase in sharing discernment relative to the Sharing-Only baseline. This means that while putting people in an accuracy mindset *increases* sharing discernment, putting people in a social-media-sharing mindset *decreases* accuracy discernment. When examining the liking and commenting responses collected in wave 2 as outcomes, the results are not significantly different from the effects observed on sharing: asking about accuracy increases discernment for sharing, liking, and commenting to similar extents (see Table S5).

Exploratory analysis finds no significant moderation of political partisanship on the effect of asking about accuracy on sharing discernment (3-way interaction between veracity, accuracy-asked and preference for the Republican party, $b = -0.063, p = 0.149$); see (Fig. 6) and Table S11.

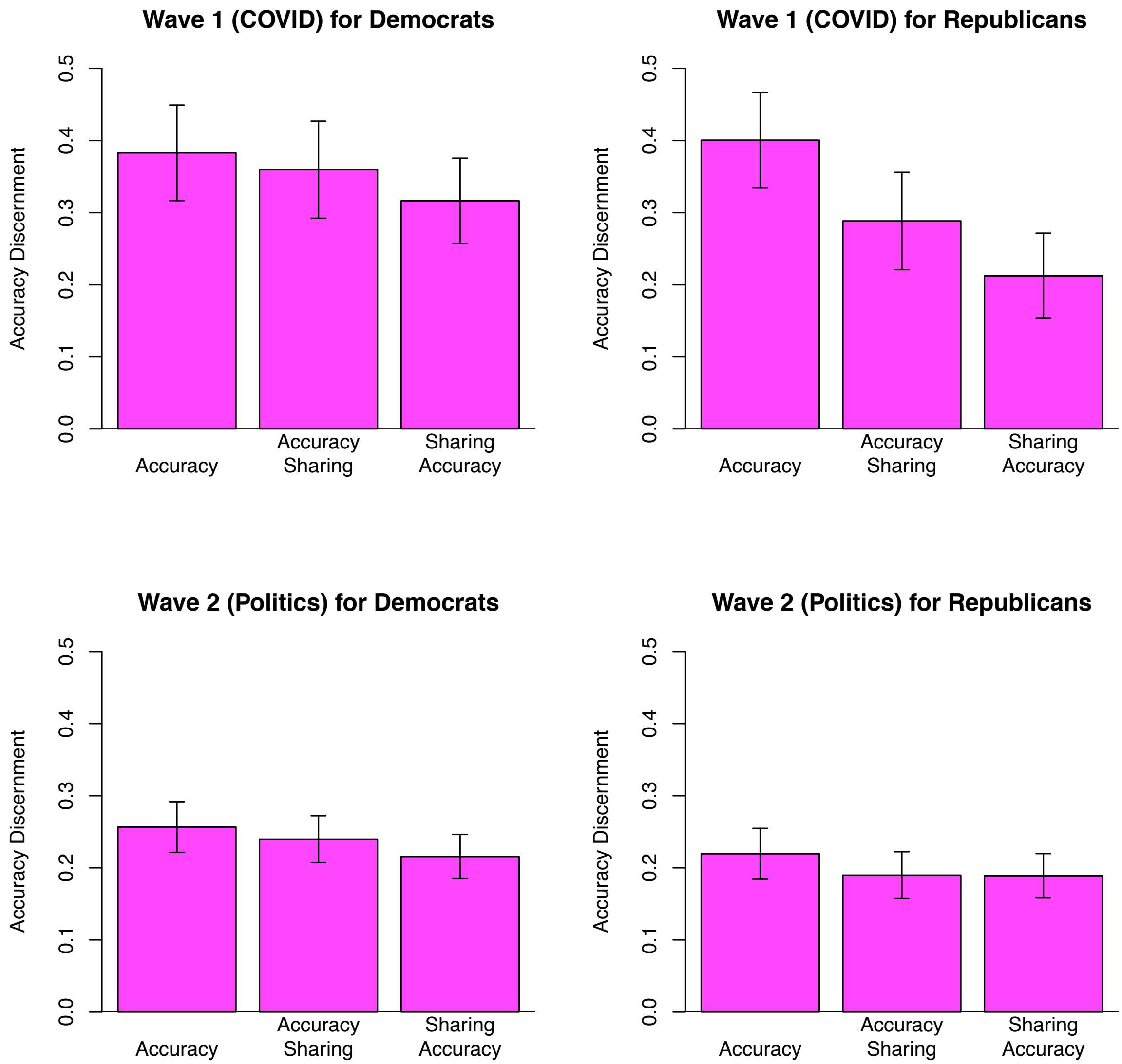

Figure 4: Accuracy discernment (perceived accuracy for true headlines minus perceived accuracy for false headlines) by condition across waves and participant partisanship. Error bars are 95% confidence intervals.

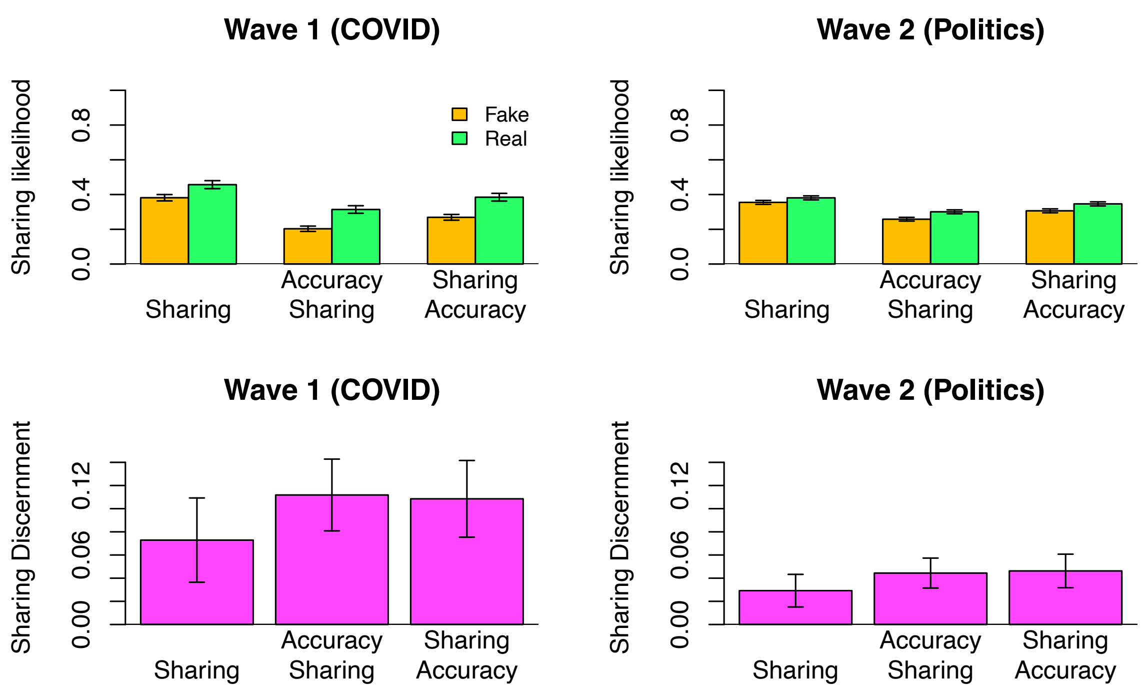

Figure 5: Top: Average sharing intentions for true (green) and false (orange) news across waves and conditions. Error bars are 95% confidence intervals. Bottom: Sharing discernment (sharing intentions for true minus sharing intentions for false) across waves and conditions. Error bars are 95% confidence intervals.

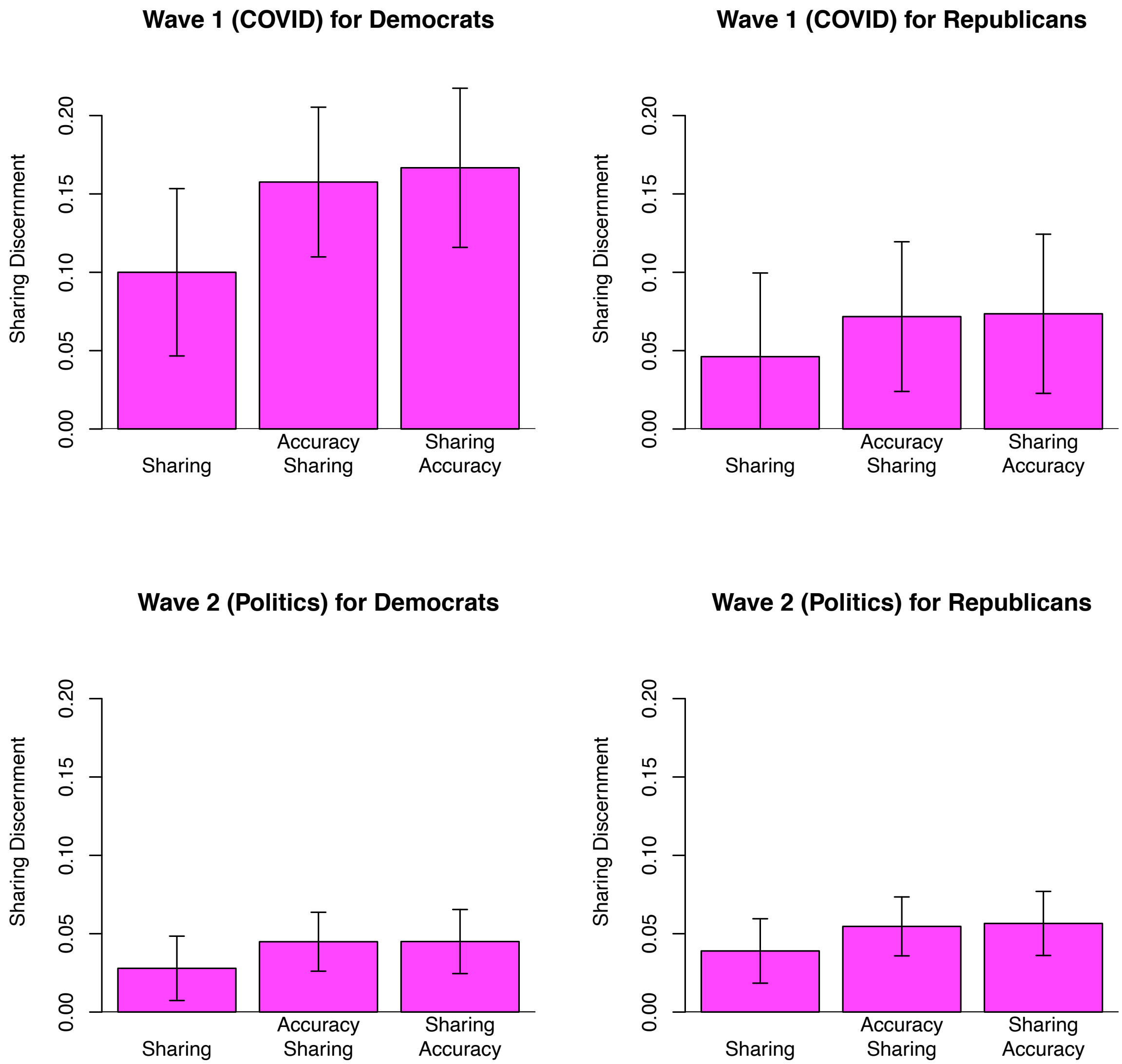

Figure 6: Sharing discernment (sharing intentions for true minus sharing intentions for false) across waves, conditions for Democrats and Republicans. Error bars are 95% confidence intervals.

Discussion

Here we found that simply asking about social media sharing meaningfully reduces participants' ability to tell truth from falsehood when judging headline accuracy. We also find evidence that this occurs because asking about sharing generally distracts people from focusing on accuracy, rather than because people are more likely to believe headlines they want to share (and vice versa). This spillover effect suggests that the social media context - and the mindset that it produces - actively interferes with accuracy discernment. It is not just that people forget to pay attention to accuracy when deciding what to share (*21*); rather, their actual underlying accuracy judgments are worse when they also consider what to share. Thus, in a similar way that asking about accuracy can induce a more accuracy-focused mindset (and therefore is an actionable intervention to increase sharing discernment (*21, 24*)), the present results indicate that asking about sharing can induce a mindset focused on social motivations (with harmful, rather than ameliorative, consequences).

Our results on accuracy discernment have important implications for the design of social media platforms. Many platforms center sharing as a principal way users interact with content. Our results suggest that this core design feature may in fact interfere with users' ability to discern truth from falsehood when trying to determine what is accurate. Future work should explore alternative design patterns that actively promote truth discernment rather than exclusively privileging engagement (*25*). This could, for example, be achieved in part by nudging users to consider the concept of accuracy while scrolling through their newsfeed (*21, 24, 26*). The context collapse of social media (*27*) could also be mitigated by organizing content and audiences thematically to delinear spaces where accuracy is (e.g. news) versus is not (e.g. family photos) central. Alternatively, platforms could emphasize the building of connections between content rather than directly sharing content with an audience. For example, platforms like Are.na (*28*) and Pinterest achieve this by allowing users to connect or pin content to channels, which does act to spread the content but through its relation to user-curated lists.

Our results on sharing discernment also have important implications for the deployment of accuracy nudges on social media platforms. While the accuracy nudge has been successfully validated numerous times (*21, 24, 26, 29*), it remains unclear how forcefully the nudge must be implemented in order to increase sharing discernment. The lack of order effect we observed for sharing discernment suggests that it is sufficient to simply prompt an accuracy mindset. In other words, prompting accuracy does not require people to actually write out accuracy for each and every item before sharing (*30*). This suggests that subtle prompts distributed across a session can effectively reduce the sharing of misinformation on social media. Our replication of the accuracy prompt effect in wave 1, where no source information was provided, also demonstrates that the accuracy prompts are doing more than just making people focus on sources.

There are several limitations of our study to consider. First, our work uses hypothetical sharing intentions, both as an outcome and as a prompt for the sharing mindset. While previous headline-level analyses have demonstrated that self-reported sharing intentions correlate highly with actual sharing on Twitter and show the same relationships between headline features and sharing rates (*31*), the actual signifiers of the sharing context are especially important for our findings. Thus, future work should investigate how particular social and design features of a sharing mindset affect truth discernment. Second, our work focuses on the U.S. news ecosystem and recruited U.S. participants. Future work should explore the cross-cultural generalizability of these results.

In sum, we have provided evidence that simply asking about social media sharing reduces truth discernment. This has important implications for social media platforms. Given that eliciting sharing is a (or arguably the) central feature of social media, our results suggest that some level of increased susceptibility to misinformation is inevitable on such platforms. This observation emphasizes the importance of developing interventions that can help users resist falsehoods when online (*32*).

Materials and methods

We conducted two waves of data collection with two similarly structured Qualtrics surveys. Our final combined dataset included a total of N=3,157 participants; mean age = 45.1, 59.8% female, 81.3% White. These participants were recruited on Lucid, which uses quota-sampling to approximate the US national distribution on age, gender, ethnicity, and geographic region (*33*). At the start of the survey, participants were asked “What type of social media accounts do you use (if any)?” and only participants who selected Facebook and/or Twitter were allowed to continue. The studies were exempted by MIT COUHES (protocol 1806400195).

In both surveys, participants were shown a series of true and false news items. The first wave used a set of 25 headlines (just text) pertaining to the COVID-19 pandemic, 15 false and 10 true. Each participant saw all 25 headlines. We conducted the first study from 7/29/2020 to 8/8/2020 (N=768). The second wave used a set of 60 news “cards” about politics presented in the format of a Facebook post (i.e., including headline, image and source). These were half true and half false, and participants were shown a random subset of 24 of these headlines. In addition to asking about sharing in the second study, we also asked participants if they would like or comment on that post (“Would you consider liking or favoriting this story online?” and “Would you consider commenting or replying to this story online?”). We conducted this second study from 10/3/2020 to 10/11/2020 (N=2,389). The full set of headlines is available at OSF at https://osf.io/ptvua/.

As shown in `(Fig. 1)`, each participant was randomly assigned to one of four conditions. In the Accuracy-Only condition, participants were asked for each headline “To the best of your knowledge, is the claim in the above headline accurate?” In the Sharing-Only condition, they were instead asked “Would you consider sharing this story online (for example, through Facebook or Twitter)?” (as in (*24*) and (*21*)). In the Accuracy-Sharing condition, participants were first asked the question about accuracy, and then on a separate the question about sharing. In the Sharing-Accuracy condition, participants were first asked the question about sharing, and then on a separate page the question about accuracy (see `(Fig. 1)`). For wave 2, all conditions with the sharing question also contained the questions about liking and commenting. All questions used binary no/yes responses and we computed both overall (mean) rates of sharing/accuracy as well as “truth discernment” (i.e., the difference between true and false, with a higher score indicating a greater mean difference). Following the main news item task, participants then completed a series of demographics and individual difference measures, including political partisanship, a digital literacy battery containing questions about familiarity with internet-related terms and attitudes towards technology (*34*), a social media literacy question asking how social media platforms decide which news stories to show them (*35*), and a ten-item procedural news knowledge battery (*36*). The data from the Accuracy-only and Sharing-Only baseline conditions of our experiment were analyzed in another publication (*37*), which examined how these individual difference measures predict discernment in.

For wave 1, the mean accuracy rating was 0.3597 with standard deviation 0.4799, the mean share rate was 0.3252 with standard deviation 0.4684 and the mean partisanship was 3.3052 with standard deviation 1.6104. For wave 2, the mean accuracy rating was 0.4125 with standard deviation 0.4923, the mean share rate was 0.3253 with standard deviation 0.4685, and the mean partisanship was 3.3472 with standard deviation 1.7436.

We completed a preregistration for wave 2 (`https://aspredicted.org/blind.php?x=uy4x3e`). We subsequently realized that our pre-registered analysis approach of using multi-level models and dropping random effects until the model converges is problematic (*38*). Thus, while we preserved the basic model structure (i.e. which terms were included in the model), we instead used linear regression with 2-way clustered errors, the analysis approach used in most of our past work, e.g. (*21, 39*). Although we did pre-register that we would test for order effects, we note that the order effect were not predicted ex ante.

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Supplementary Materials
for
The social media context interferes with truth discernment

August 26, 2022

1 Models predicting accuracy evaluations

As discussed in the main text, we fit a linear model at the rating level to predict accuracy evaluations. The pooled model includes condition dummies (Sharing-asked and order), a veracity dummy, a wave dummy and all interactions. We use two-way sandwich clustered errors.

The model in Table S1 shows a significant three-way interaction between veracity, sharing-asked, and wave ($p < 0.001$). Therefore, we consider the two waves separately, and run a separate model for each.

Table S1: Linear model predicting accuracy evaluation across both waves. We use a headline veracity dummy variable (0=false, 1=true), and sharing-asked dummy variable indicating whether the participant rated sharing as well as accuracy (0=Accuracy only, 1=Accuracy-Sharing or Sharing-Accuracy), an order dummy variable indicating the order of the two ratings for conditions where both accuracy and sharing were asked (center-coded: -0.5=Accuracy-Sharing, 0.5=Sharing-Accuracy, 0=Accuracy only), and a z-scored wave dummy.

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	0.276	0.005	58.047	0.000
veracity	0.271	0.007	37.343	0.000
scale(wave)	0.034	0.004	8.095	0.000
sharing-asked	0.019	0.006	3.277	0.001
order	0.029	0.007	4.292	0.000
veracity:scale(wave)	-0.072	0.007	-10.132	0.000
veracity:sharing-asked	-0.052	0.009	-5.876	0.000
veracity:order	-0.037	0.010	-3.572	0.000
scale(wave):sharing-asked	0.000	0.005	0.033	0.974
scale(wave):order	-0.004	0.006	-0.629	0.530
veracity:scale(wave):sharing-asked	0.031	0.009	3.518	0.000
veracity:scale(wave):order	0.018	0.010	1.689	0.091

The model specification for wave 1 is identical to the pooled analysis, except that it subsets on wave 1 data and does not include the wave dummy.

Since wave 2 involved political headlines, when subsetting on wave 2 we also include subject partisanship and political concordance in the model (as per our pre-registration).

2 Models predicting sharing intentions

As discussed in the main text, we fit a linear regression predicting sharing intentions. Like the pooled accuracy evaluation model, the sharing intention model includes condition dummies (accuracy-asked and order), a veracity dummy, a wave dummy and all interactions.

Table S2: Linear model predicting accuracy evaluation for wave 1 (COVID). We use a headline veracity dummy variable (0=false, 1=true), and sharing-asked dummy variable indicating whether the participant rated sharing as well as accuracy (0=Accuracy only, 1=Accuracy-Sharing or Sharing-Accuracy), and an order dummy variable indicating the order of the two ratings for conditions where both accuracy and sharing were asked (center-coded: -0.5=Accuracy-Sharing, 0.5=Sharing-Accuracy, 0=Accuracy only).

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	0.219	0.008	28.749	0.000
veracity	0.389	0.013	29.064	0.000
sharing-asked	0.019	0.010	1.970	0.049
order	0.036	0.012	3.078	0.002
veracity:sharing-asked	-0.103	0.017	-6.158	0.000
veracity:order	-0.066	0.020	-3.265	0.001

Next we look for differential patterns of engagement for the "sharing" outcome relative to liking and commenting in wave 2. To do so, we reshape the sharing data into a long format, with three rows for each participant-item pair, corresponding to the three types of engagement the participant indicated for that item. This model model includes condition dummies (accuracy-asked and order), a veracity dummy, engagement type dummies (taking sharing as the held-out baseline), and all interactions.

3 Moderation Analyses

To measure political partisanship, we asked participants "Which of the following best describes your political preference?" with answers from 1=Strongly Democratic to 6=Strongly Republican.

We build on the Table S3 by looking at the potential moderator of political partisanship on both accuracy evaluations and sharing decisions.

Table S3: Linear model predicting accuracy evaluation for wave 2 (politics). We use a headline veracity dummy variable (0=false, 1=true), and sharing-asked dummy variable indicating whether the participant rated sharing as well as accuracy (0=Accuracy only, 1=Accuracy-Sharing or Sharing-Accuracy), and an order dummy variable indicating the order of the two ratings for conditions where both accuracy and sharing were asked (center-coded: -0.5=Accuracy-Sharing, 0.5=Sharing-Accuracy, 0=Accuracy only).

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	0.283	0.006	46.370	0.000
sharing-asked	0.024	0.007	3.168	0.002
order	0.016	0.009	1.836	0.066
veracity	0.243	0.009	26.827	0.000
scale(republican)	0.028	0.007	4.243	0.000
concord	0.053	0.012	4.368	0.000
sharing-asked:veracity	-0.035	0.011	-3.146	0.002
order:veracity	-0.021	0.013	-1.680	0.093
sharing-asked:scale(republican)	-0.023	0.008	-2.875	0.004
order:scale(republican)	0.014	0.009	1.559	0.119
veracity:scale(republican)	-0.032	0.009	-3.394	0.001
sharing-asked:concord	-0.013	0.015	-0.894	0.371
order:concord	-0.024	0.017	-1.408	0.159
veracity:concord	-0.024	0.018	-1.348	0.178
scale(republican):concord	-0.003	0.013	-0.212	0.832
sharing-asked:veracity:scale(republican)	0.011	0.011	0.973	0.331
order:veracity:scale(republican)	0.021	0.013	1.603	0.109
sharing-asked:veracity:concord	0.033	0.022	1.496	0.135
order:veracity:concord	-0.010	0.025	-0.406	0.685
sharing-asked:scale(republican):concord	0.011	0.016	0.710	0.477
order:scale(republican):concord	-0.008	0.018	-0.441	0.660
veracity:scale(republican):concord	0.039	0.019	2.076	0.038
sharing-asked:veracity:scale(republican):concord	-0.026	0.023	-1.154	0.249
order:veracity:scale(republican):concord	-0.018	0.026	-0.700	0.484

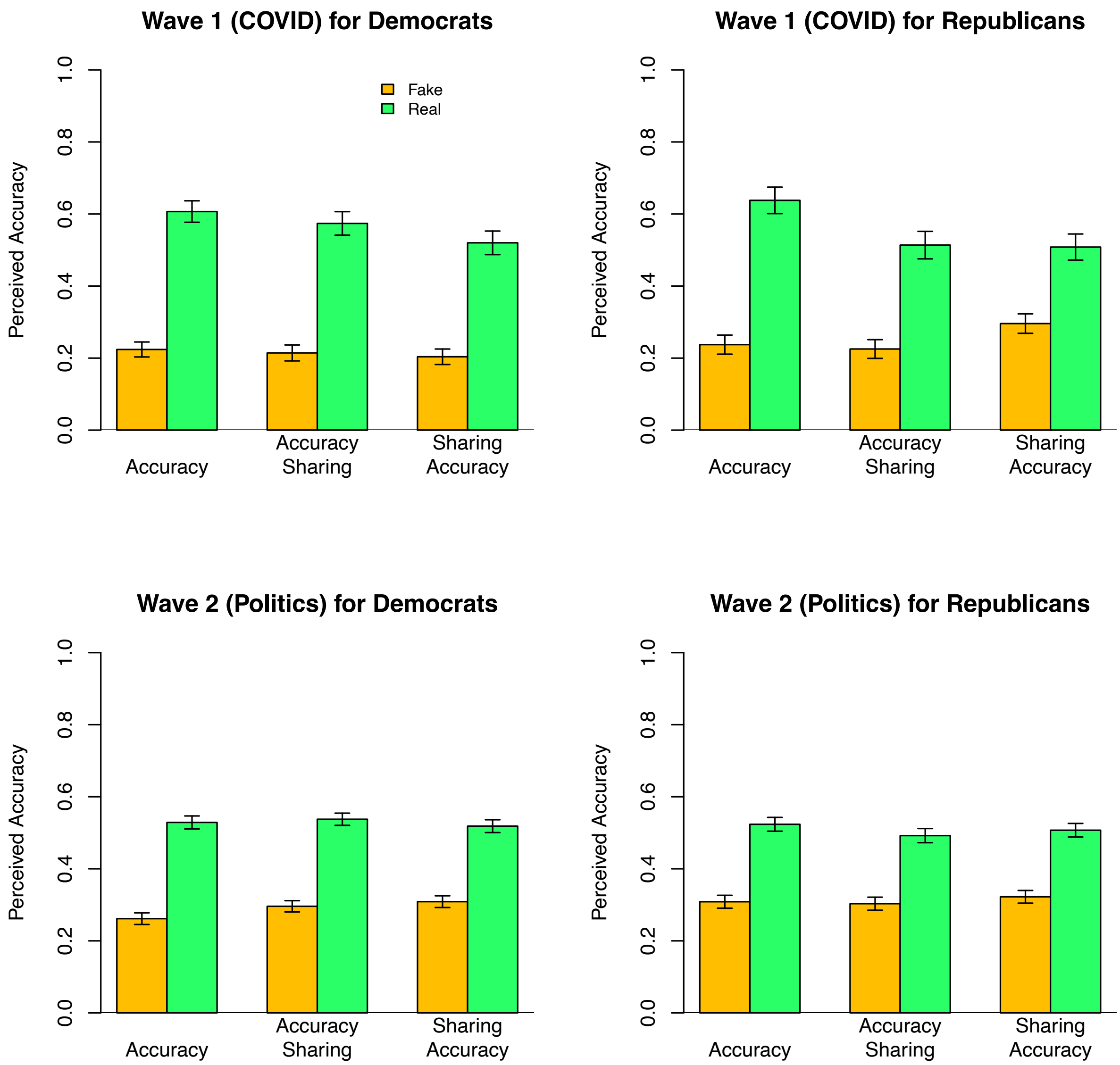

Figure S1: Average perceived accuracy of true (green) and false (yellow) news across waves and conditions for Democrats and Republicans. Error bars are standard errors.

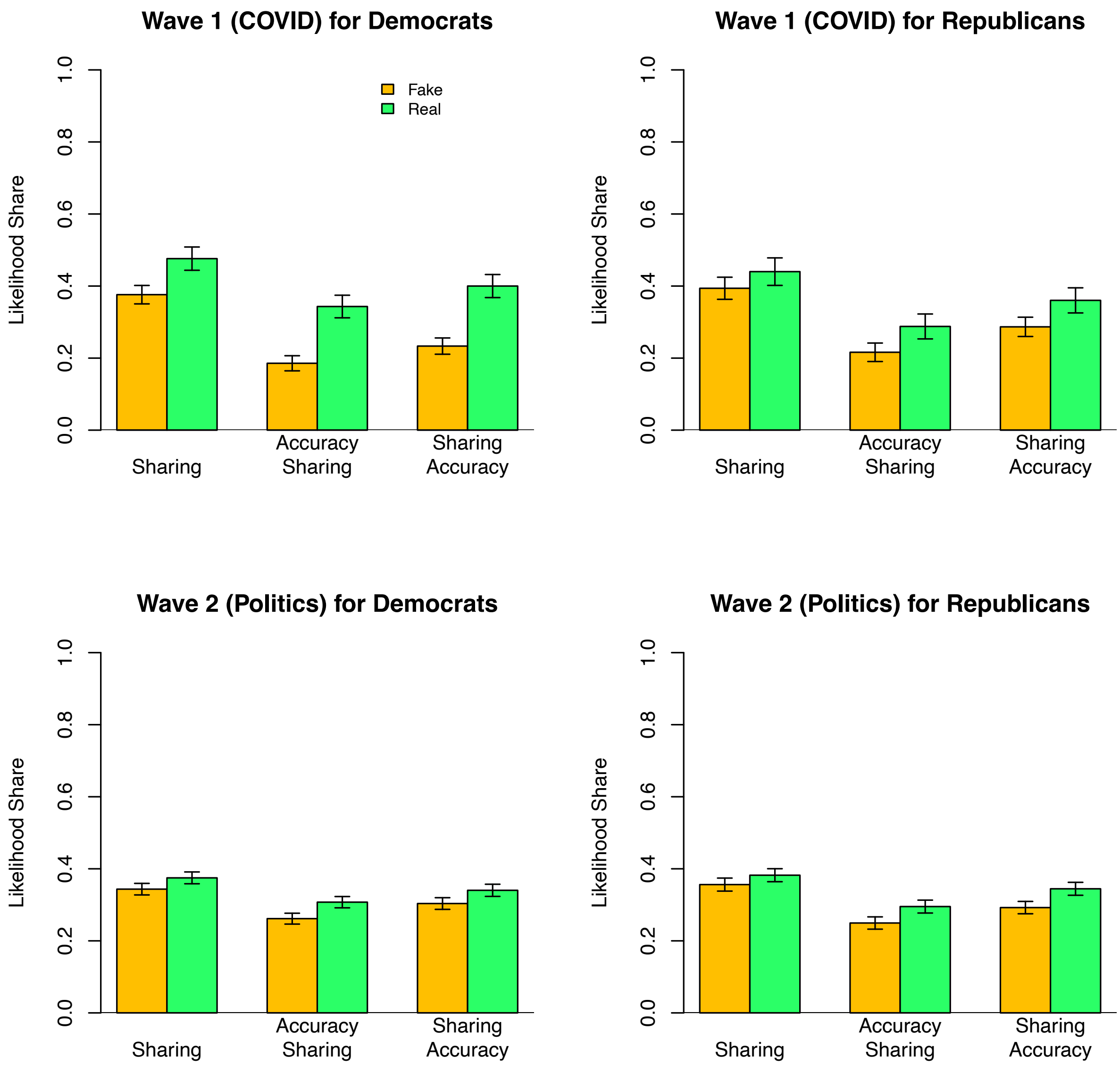

Figure S2: Average sharing intent of true (green) and false (yellow) news across waves and conditions for Democrats and Republicans. Error bars are standard errors.

Table S4: Linear model predicting sharing sharing intention across waves. We use a headline veracity dummy variable (0=false, 1=true), and an accuracy-asked dummy variable indicating whether the participant rated accuracy as well as sharing (0=Sharing only, 1=Accuracy-Sharing or Sharing-Accuracy), an order dummy variable indicating the order of the two ratings for conditions where both accuracy and sharing were asked (center-coded: -0.5=Accuracy-Sharing, 0.5=Sharing-Accuracy, 0=Accuracy only), and a z-scored wave dummy.

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	0.362	0.005	72.958	0.000
accuracy-asked	-0.091	0.006	-15.349	0.000
order	0.053	0.007	8.006	0.000
veracity	0.039	0.007	5.331	0.000
scale(wave)	-0.012	0.005	-2.437	0.015
accuracy-asked:veracity	0.021	0.009	2.396	0.017
order:veracity	-0.001	0.010	-0.085	0.932
accuracy-asked:scale(wave)	0.032	0.006	5.607	0.000
order:scale(wave)	-0.008	0.006	-1.249	0.212
veracity:scale(wave)	-0.021	0.007	-2.866	0.004
accuracy-asked:veracity:scale(wave)	-0.010	0.009	-1.122	0.262
order:veracity:scale(wave)	-0.003	0.010	-0.343	0.731

Table S5: Linear model predicting engagement relative to sharing.

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	0.355	0.006	60.729	0.000
accuracy-asked	-0.073	0.007	-10.274	0.000
order	0.048	0.008	6.083	0.000
veracity	0.026	0.008	3.146	0.002
liking	-0.024	0.008	-2.874	0.004
commenting	0.013	0.008	1.599	0.110
accuracy-asked:veracity	0.015	0.010	1.500	0.134
order:veracity	-0.003	0.011	-0.248	0.804
accuracy-asked:liking	0.007	0.010	0.736	0.462
accuracy-asked:commenting	-0.005	0.010	-0.484	0.629
order:liking	-0.001	0.011	-0.063	0.950
order:commenting	-0.013	0.011	-1.133	0.257
veracity:liking	0.005	0.012	0.418	0.676
veracity:commenting	-0.006	0.012	-0.527	0.598
accuracy-asked:veracity:liking	0.007	0.014	0.469	0.639
accuracy-asked:veracity:commenting	0.003	0.014	0.198	0.843
order:veracity:liking	-0.004	0.016	-0.255	0.799
order:veracity:commenting	0.001	0.016	0.070	0.944

Table S6: Item-level linear model predicting effect of sharing first on accuracy. Sharability is the likelihood of sharing in the share-only condition.

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	0.042	0.043	0.972	0.331
sharability	-0.035	0.113	-0.313	0.754
veracity	-0.071	0.012	-5.720	0.000
wave	-0.033	0.014	-2.403	0.016

Table S7: Item-level linear model predicting effect of sharing first on accuracy. Baseline_acc is the perceived accuracy in the accuracy-only condition.

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	0.124	0.015	8.115	0.000
baseline_acc	-0.355	0.051	-6.916	0.000
veracity	0.025	0.017	1.460	0.144
wave	-0.038	0.010	-3.748	0.000

Table S8: Linear model predicting accuracy judgements with continuous political partisanship moderator.

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	0.269	0.005	53.663	0.000
veracity	0.282	0.008	36.722	0.000
scale(wave)	0.024	0.005	5.236	0.000
sharing-asked	0.018	0.006	2.980	0.003
order	0.019	0.007	2.668	0.008
scale(republican)	0.019	0.005	3.518	0.000
veracity:scale(wave)	-0.065	0.008	-8.575	0.000
veracity:sharing-asked	-0.050	0.009	-5.275	0.000
veracity:order	-0.031	0.011	-2.868	0.004
scale(wave):sharing-asked	0.009	0.006	1.597	0.110
scale(wave):order	-0.005	0.007	-0.720	0.471
veracity:scale(republican)	-0.024	0.008	-3.031	0.002
scale(wave):scale(republican)	0.014	0.005	2.828	0.005
sharing-asked:scale(republican)	-0.007	0.006	-1.151	0.250
order:scale(republican)	0.026	0.007	3.591	0.000
veracity:scale(wave):sharing-asked	0.025	0.009	2.660	0.008
veracity:scale(wave):order	0.017	0.011	1.543	0.123
veracity:scale(wave):scale(republican)	-0.013	0.008	-1.579	0.114
veracity:sharing-asked:scale(republican)	-0.003	0.010	-0.294	0.768
veracity:order:scale(republican)	0.008	0.011	0.702	0.482
scale(wave):sharing-asked:scale(republican)	-0.025	0.006	-4.091	0.000
scale(wave):order:scale(republican)	-0.021	0.007	-2.887	0.004
veracity:scale(wave):sharing-asked:scale(republican)	0.022	0.010	2.181	0.029
veracity:scale(wave):order:scale(republican)	0.023	0.012	1.932	0.053

Table S9: Linear model predicting accuracy judgements with continuous political partisanship moderator for wave 1 (COVID)

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	0.229	0.008	27.429	0.000
veracity	0.390	0.014	26.912	0.000
sharing-asked	0.003	0.010	0.251	0.802
order	0.025	0.012	2.081	0.037
scale(republican)	-0.004	0.009	-0.494	0.622
veracity:sharing-asked	-0.090	0.018	-4.991	0.000
veracity:order	-0.059	0.022	-2.732	0.006
veracity:scale(republican)	-0.003	0.015	-0.206	0.837
sharing-asked:scale(republican)	0.032	0.011	2.965	0.003
order:scale(republican)	0.057	0.013	4.462	0.000
veracity:sharing-asked:scale(republican)	-0.036	0.018	-1.988	0.047
veracity:order:scale(republican)	-0.028	0.022	-1.271	0.204

Table S10: Linear model predicting accuracy judgements with continuous political partisanship moderator for wave 2 (political)

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	0.283	0.006	46.313	0.000
veracity	0.243	0.009	26.760	0.000
sharing-asked	0.024	0.007	3.153	0.002
order	0.016	0.009	1.878	0.060
scale(republican)	0.028	0.007	4.240	0.000
veracity:sharing-asked	-0.035	0.011	-3.120	0.002
veracity:order	-0.021	0.013	-1.640	0.101
veracity:scale(republican)	-0.032	0.009	-3.438	0.001
sharing-asked:scale(republican)	-0.023	0.008	-2.917	0.004
order:scale(republican)	0.014	0.009	1.589	0.112
veracity:sharing-asked:scale(republican)	0.010	0.011	0.919	0.358
veracity:order:scale(republican)	0.022	0.013	1.707	0.088

Table S11: Linear model predicting accuracy judgements with binary political partisanship moderator for wave 1 (political)

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	0.230	0.008	27.394	0.000
veracity	0.390	0.015	26.913	0.000
sharing-asked	0.001	0.010	0.113	0.910
order	0.024	0.012	1.939	0.052
scale(republican_binary)	0.007	0.008	0.781	0.435
veracity:sharing-asked	-0.089	0.018	-4.947	0.000
veracity:order	-0.057	0.022	-2.651	0.008
veracity:scale(republican_binary)	0.009	0.015	0.596	0.551
sharing-asked:scale(republican_binary)	0.019	0.010	1.797	0.072
order:scale(republican_binary)	0.040	0.012	3.278	0.001
veracity:sharing-asked:scale(republican_binary)	-0.052	0.018	-2.860	0.004
veracity:order:scale(republican_binary)	-0.016	0.021	-0.755	0.450

Table S12: Linear model predicting accuracy judgements with binary political partisanship moderator for wave 2 (political)

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	0.283	0.006	46.240	0.000
veracity	0.243	0.009	26.815	0.000
sharing-asked	0.024	0.007	3.217	0.001
order	0.016	0.009	1.831	0.067
scale(republican_binary)	0.023	0.006	3.820	0.000
veracity:sharing-asked	-0.035	0.011	-3.196	0.001
veracity:order	-0.019	0.013	-1.527	0.127
veracity:scale(republican_binary)	-0.026	0.009	-2.866	0.004
sharing-asked:scale(republican_binary)	-0.018	0.007	-2.437	0.015
order:scale(republican_binary)	0.003	0.009	0.363	0.716
veracity:sharing-asked:scale(republican_binary)	0.007	0.011	0.607	0.544
veracity:order:scale(republican_binary)	0.014	0.013	1.091	0.275

Table S13: Linear model predicting sharing decisions with political partisanship moderator

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	0.416	0.021	19.788	0.000
veracity	0.125	0.033	3.731	0.000
accuracy-asked	-0.238	0.025	-9.660	0.000
order	0.075	0.026	2.935	0.003
scale(republican)	-0.034	0.023	-1.482	0.138
wave	-0.033	0.012	-2.819	0.005
veracity:accuracy-asked	0.077	0.040	1.922	0.055
veracity:order	0.011	0.043	0.249	0.803
veracity:scale(republican)	-0.025	0.036	-0.694	0.488
accuracy-asked:scale(republican)	0.091	0.027	3.344	0.001
order:scale(republican)	0.038	0.029	1.305	0.192
veracity:wave	-0.048	0.018	-2.618	0.009
accuracy-asked:wave	0.083	0.014	5.971	0.000
order:wave	-0.017	0.015	-1.148	0.251
scale(republican):wave	0.025	0.013	1.961	0.050
veracity:accuracy-asked:scale(republican)	-0.063	0.044	-1.443	0.149
veracity:order:scale(republican)	-0.023	0.048	-0.475	0.635
veracity:accuracy-asked:wave	-0.030	0.022	-1.382	0.167
veracity:order:wave	-0.006	0.024	-0.261	0.794
veracity:scale(republican):wave	0.012	0.020	0.600	0.549
accuracy-asked:scale(republican):wave	-0.056	0.015	-3.682	0.000
order:scale(republican):wave	-0.009	0.016	-0.584	0.559
veracity:accuracy-asked:scale(republican):wave	0.032	0.024	1.338	0.181
veracity:order:scale(republican):wave	0.016	0.026	0.602	0.547

Table S14: Linear model predicting accuracy judgements with binary political partisanship moderator.

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	0.268	0.005	53.517	0.000
veracity	0.283	0.008	36.768	0.000
scale(wave)	0.023	0.005	5.051	0.000
sharing-asked	0.018	0.006	2.997	0.003
order	0.018	0.007	2.592	0.010
scale(republican_binary)	0.019	0.005	3.754	0.000
veracity:scale(wave)	-0.065	0.008	-8.562	0.000
veracity:sharing-asked	-0.051	0.009	-5.368	0.000
veracity:order	-0.030	0.011	-2.737	0.006
scale(wave):sharing-asked	0.010	0.006	1.735	0.083
scale(wave):order	-0.004	0.007	-0.672	0.502
veracity:scale(republican_binary)	-0.017	0.008	-2.152	0.031
scale(wave):scale(republican_binary)	0.007	0.005	1.587	0.112
sharing-asked:scale(republican_binary)	-0.008	0.006	-1.335	0.182
order:scale(republican_binary)	0.013	0.007	1.852	0.064
veracity:scale(wave):sharing-asked	0.025	0.009	2.663	0.008
veracity:scale(wave):order	0.017	0.011	1.532	0.126
veracity:scale(wave):scale(republican_binary)	-0.015	0.008	-2.007	0.045
veracity:sharing-asked:scale(republican_binary)	-0.009	0.009	-0.969	0.332
veracity:order:scale(republican_binary)	0.006	0.011	0.521	0.602
scale(wave):sharing-asked:scale(republican_binary)	-0.016	0.006	-2.875	0.004
scale(wave):order:scale(republican_binary)	-0.017	0.007	-2.482	0.013
veracity:scale(wave):sharing-asked:scale(republican_binary)	0.026	0.009	2.762	0.006
veracity:scale(wave):order:scale(republican_binary)	0.013	0.011	1.203	0.229