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The effect of accuracy instructions on Coronavirus-related belief change following conversational interactions

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Abstract
In a high-risk environment, such as during an epidemic, people are exposed to a large amount of information, both accurate and inaccurate. Following exposure, they typically discuss the information with each other. Here, we assess the effects of such conversations on beliefs. A sample of 126 M-Turk participants rated the accuracy of a set of COVID-19 statements, including accurate information, inaccurate information, and conspiracy theories (pre-test). They were then paired and asked to discuss these statements (low epistemic condition) or to discuss only the statements they thought were accurate (high epistemic condition). Finally, they rated the accuracy of the initial statements again (post-test). We do not find an effect of the epistemic condition on belief change. However, we find that individuals are sensitive to their conversational partners and change their beliefs according to their partners' conveyed beliefs. In exploratory analyses, we report predictors of believing COVID-19 conspiracies.

KEYWORDS
belief change, conspiracy beliefs, conversational interactions, COVID-19

1 | INTRODUCTION

With the rise of globalization, infectious diseases have proven more and more far-reaching (Saker et al., 2004). There is hardly a year without the emergence of a highly threatening pandemic, from H1N1 (swine flu) in 2009, to Ebola in 2014, to the Zika virus in 2017, and to COVID-19 in 2020. Fighting an epidemic involves not only developing effective treatments and ensuring wide distribution, but also informing the public of the symptoms, protective measures, and treatments associated with the disease. It becomes critically important, thus, to understand how information is acquired and incorporated into the people's belief systems, and how these belief systems change after interacting with one another (Brandt & Sleegers, 2021).

Prior work shows that when individuals learn about an epidemic, they engage in behaviors aimed at acquiring information, such as turning to news and social media for relevant content (Frenkel et al., 2020; Saker et al., 2004). Subsequently, after being exposed to such large amounts of crisis-relevant information, people typically discuss the acquired information with each other (Liu et al., 2013). The communicative act of discussing information has been shown to influence the people's memory of the studied information (Cuc et al., 2007; Hirst & Echterhoff, 2012), which in turn was found to impact the believability of information (Fazio et al., 2015; Hasher et al., 1977; Vlasceanu & Coman, 2018). Given that these communicative interactions shape what people believe, one strategy to diminish the believability of misinformation and to encourage the dissemination of accurate information (van der Linden, 2021; van der Linden et al., 2021), might be to impose a higher threshold for both communicating and accepting information (Pennycook et al., 2021; Roozenbeek et al., 2021). This higher threshold could be created through instructions involving high epistemic accuracy, such as encouraging people to question the veracity of information before communicating (Lewandowsky et al., 2012) or sharing (Pennycook et al., 2021) information. Prior studies, however, typically involve individual-level paradigms. Here, we assess the effectiveness of deploying this epistemic strategy on free-flowing communicative interactions, and, in turn, the impact of these interactions on the people's beliefs.

Moreover, given that public health emergencies are high risk, uncertain situations that increase anxiety and the need for security (Douglas et al., 2017; Douglas et al., 2019) might facilitate inaccurate information to spread, mainly because people do not have the cognitive resources to assess the veracity of the information they receive (Coman & Berry, 2015). A large body of psychological research shows that information is differentially processed by the cognitive system depending on the emotional state of the recipients (Rozin & Royzman, 2001). Contexts high in emotionality result in high information propagation rates (Harber & Cohen, 2005), in "viral" successes (Berger & Milkman, 2012), and in communicative advantages in dyadic interactions (Nyhof & Barrett, 2001). Relatedly, uncertainty and loss of control have been found to facilitate the emergence of conspiracy theories (Uscinski & Parent, 2014; Nefes, 2014; Whitson & Galinsky, 2008; but see: Douglas et al., 2017; Douglas et al., 2019; Stojanov et al., 2020). These findings showcase the impact of emotional states and motivations to increase psychological safety created by high-risk and high-uncertainty contexts on information propagation. Thus, in the current study, we are incorporating this factor by conducting the experiment during the COVID-19 pandemic, and focusing on COVID-19 information acquisition and transfer.

To investigate the effects of conversational interactions on the people's beliefs during a high-risk high-uncertainty environment caused by a global health crisis, we designed an experiment in which participants first rated the accuracy of a set of statements about COVID-19 (accurate, inaccurate, and conspiracies) and filled out a series of motivation scales. Then, they were assigned to pairs, and were asked to discuss the statements with each other, in 5-min dyadic conversations. To manipulate the likelihood of individuals sharing accurate information in their conversational interactions, the instructions encouraged a random subset of the pairs to discuss any piece of information from the study (low epistemic accuracy condition), and the other subset of the pairs to discuss only the pieces of information they were confident were correct (high epistemic accuracy condition). Lastly, participants rated again the believability of the initial statements and their motivations (e.g., need for psychological security).

Our first hypothesis was that participants in the high epistemic accuracy condition would become more knowledgeable than those in the low epistemic accuracy condition, given that the focus of their conversations would be on the accurate rather than on the inaccurate information or conspiracies. Our second hypothesis was that participants would be sensitive to their conversational partners' beliefs expressed during their conversations and adjust their own beliefs accordingly. Based on previous research (Vlasceanu & Coman, 2018) we also hypothesized this adjustment would be strongest in the case of initially moderately held beliefs. In exploratory analyses, for which we did not have a priori hypotheses, we tested the predictors of COVID-19 knowledge and conspiracy endorsement in models that included trust in politicians/experts, media consumption, social media engagement, threat and anxiety, and positive and negative emotional states.

2 | METHOD

2.1 | Open science practices

The data and stimulus materials can be found on our open science framework page at https://osf.io/sk4dt/?

The data analysis (in Python and R) can be accessed as a jupyter notebook on Github at https://github.com/mvlasceanu/coviddyad

2.2 | Participants

We recruited a total of 140 participants using the Amazon Mechanical Turk platform. Participants were compensated at the platform's standard rate. The study was approved by the Institutional Review Board at Princeton University. After discarding participants who failed the pre-established attention checks (e.g., "Please select option 2 if you are still reading these questions."), data from the final sample of 126 participants (61% women; $M_{age} = 37.84$, $SD_{age} = 11.35$) were included in our individual level statistical analyses (i.e., exploratory analyses). Of the 126 participants who passed the attention checks, 8 had conversational partners that dropped out of the study after the conversation. Therefore, we had complete data from 59 pairs of participants (118 participants), which were included in the dyadic level statistical analyses. In the dyadic level analyses, we accounted for the participants' interdependence rendered by the conversational phase. Therefore, for the dyadic level analyses, we had 80% power (computed using the Pingouin open-source statistical package in Python; Vallat, 2018), to detect an effect size (Cohen's d) of 0.4 at a significance level of .05 in a repeated measures ANOVA.

2.3 | Stimulus materials

We undertook preliminary studies to develop a set of 22 statements regarding COVID-19. A pilot study was conducted on separate sample of 269 Cloud Research workers ($M_{age} = 40.63$, $SD_{age} = 15.49$; 66% women) to select these statements from a larger initial set of 37 statements. For each of these statements, we collected believability ratings (i.e., "How accurate or inaccurate do you think this statement is?" on a scale from 0—extremely inaccurate to 100—extremely accurate). The 22 statements we selected were on average moderately endorsed ($M = 51.95$, $SD = 20.08$, on a 0 to 100-point scale). In reality, 9 of them are actually accurate (e.g., "The sudden loss of smell or taste is a symptom of being infected with COVID-19"), 9 are inaccurate (e.g., "Antibiotics can kill COVID-19"), and 4 are conspiracies (e.g., "COVID-19 was built as an intended bioweapon"), as concluded by published scientific papers and/or by the CDC at the time of data collection (i.e., May 2020). Of note, conspiracies differ from inaccurate statements by assuming nefarious intent and being immune to evidence (Lewandowsky & Cook, 2020).

2.4 | Design and procedure

The data were collected in May 2020. The 126 participants went through five experimental phases. Participants were told they would participate in an experiment about the people's evaluation of information and were directed to the survey on SoPHIE (i.e., Software Platform for Human Interaction Experiments) a platform that allows free-flowing computer-mediated interactions among participants. After completing the informed consent form, participants were directed to a pre-evaluation phase, in which they rated a set of 22 statements (one on each page) by indicating the degree to which they believed each statement (i.e., "How accurate do you think this statement is," from 1—extremely inaccurate to 10—extremely accurate). Then, participants were asked to fill a series of scales aimed at capturing the need for psychological security (see Measures). A conversational phase followed, in which participants were randomly paired in groups of two and were instructed to discuss the information from the pre-test phase with another participant, in a 5-min dyadic conversation. The instructions encouraged a random subset of the pairs to discuss any piece of information from the study ($N = 58$; low epistemic condition): "In what follows you will have a chat conversation with another participant who answered the same questions about COVID-19 like yourself. In this conversation, please discuss the information about COVID-19 we asked about at the beginning of this study. As you mention a piece of information please is as specific as possible so that your conversational partner can identify what information you are referring to." The other subset of the pairs was asked to discuss only the pieces of information they were confident were correct ($N = 68$; high epistemic condition): "In what follows you will have a chat conversation with another participant who answered the same questions about COVID-19 like yourself. In this conversation, please discuss the information about COVID-19 we asked about at the beginning of this study. Importantly, only discuss information you believe is true and correct the other participant if they bring up information you believe is false. As you mention a piece of information please be as specific as possible so that your conversational partner can identify what information you are referring to." Conversations took the form of interactive exchanges in a chat-like computer-mediated environment in which participants typed their responses. In the next phase (post-test), participants rated again the believability of the initial 22 statements. Finally, participants rated again the initial series of scales, after which they were asked to complete a demographic questionnaire and were debriefed.

2.5 | Measures

Statement endorsement was measured at pre-test and post-test with the question "How accurate or inaccurate do you think this statement is?", on a scale from 0—extremely inaccurate to 10—extremely accurate.

The motivation for psychological security scales included *COVID-19 anxiety*, measured in the pre-motivation and post-motivation phase with the question "How anxious are you about the COVID-19 pandemic?" on a scale from 0—Not at all to 100—Extremely.

Moreover, *dynamic anxiety* was measured by the question "Would you say that during the past 6 weeks you have become more or less anxious about the COVID-19 pandemic?" on a scale from 1—much less anxious to 7—much more anxious. We only measured dynamic anxiety in the pre-motivation phase.

We also measured ***COVID-19 threat***, with the question "How threatening is the COVID-19 pandemic?" from 0—not at all to 10—extremely.

Finally, we included a short version of the *Positive and Negative Affect Schedule* (PANAS; Watson, Clark, & Tellegen, 1988), featuring eight emotions: *Calm, Tense, Relaxed, Worried, Content, Fearful, Hopeful, Anxious, and Lonely*. The instructions were: "Read each statement and select the appropriate response to indicate how you feel right now, that is, at this moment. There are no right or wrong answers. Do not spend too much time on any one statement and give the answer which seems to describe your present feelings best" and participants rated each emotion from 0—not at all to 5—extremely. In our analyses, we aggregated the four positive emotions and the five negative emotions to create a measure of PANAS positive emotions (Cronbach's alpha 0.84) and one of PANAS negative emotions (Cronbach's alpha 0.87).

Given prior work on the impact of social media on misinformation spread (Van Bavel et al., 2020; Van Bavel & Pereira, 2018; Vosoughi et al., 2018; Wang et al., 2019) we also measured the participants' *news media* and *social media* usage. We included these measures as part of the demographic section at the end of the experiment. Engagement with news media was measured with the question "During a regular day the last 2 weeks, how many hours a day have you been watching the following media outlets (approximate to whole number)" on a scale from 0 (0 h) to 5 (5 or more hours). We included the following media outlets: *MSNBC*, *CNN*, *FOX*, *ABC*, *NBC*, *CBS*, and *PBS/NPR*. In our analyses, we used both the individual media outlet data as well as the aggregated score of all seven media outlets. The aggregated score consisted of the sum of all the answers on each of the seven scales, creating a single news media measure.

Similarly, for social media, we asked participants "During a regular day the last 2 weeks, how many minutes a day have you been on the following social media platforms (approximate to whole number)" on a scale from 0 (0 min) to 10 (100 min *or more*). The social media platforms we included were *Facebook*, *Instagram*, *Twitter*, and *Snapchat*. We aggregated these four social media platforms in our analyses by summing all the answers on each of these scales to create a single social media measure.

Also in the demographic section, given prior work showing the impact of support for President Trump on rational belief update (Vlasceanu et al., 2021a, 2021b), we measured the participants' *trust in President Trump* with the question "How much do you trust the COVID-19 information provided by President Trump?" and *trust in Dr. Fauci* with the question "How much do you trust the COVID-19 information provided by Doctor Anthony Fauci, the director of the National Institute of Allergy and Infectious Diseases?" on a scale from 0–not at all to 10—extremely.

Finally, we asked participants to indicate their *age* ("What is your age?"), *gender* ("What is your gender?"), *education* ("What is your level of education?"), and *political orientation* ("What political party best aligns with your views?").

2.6 | Analysis and coding

Here, a *belief* is operationalized as the endorsement of a statement (i.e., either accurate, inaccurate, or conspiratorial) (Table 1).

Belief change was computed as the participants' statement endorsement at post-test minus endorsement at pre-test (Table 1). Therefore, we note that even though participants scored their beliefs on a 0–10 scale, a belief *change* score could go from −10 to 10.

Participants' *knowledge* about COVID-19 was computed as the difference between their endorsement of the accurate and the inaccurate information (i.e., belief in accurate minus belief in inaccurate information) (Table 1). Participants' COVID-19 *conspiracy* endorsement was analyzed separately (Table 1).

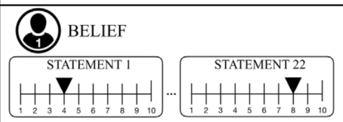
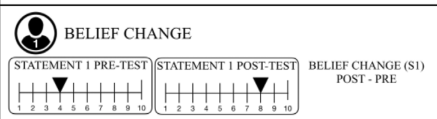
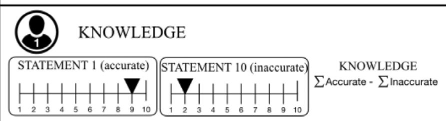
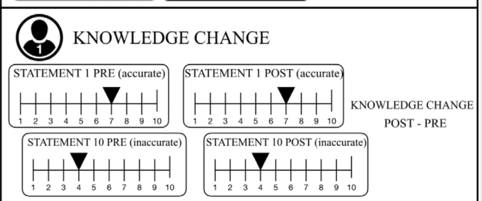
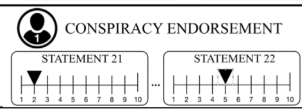
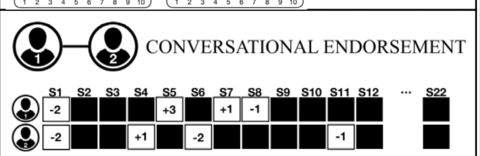
The conversations' content was coded for *conversational endorsement* (Table 1). This entailed marking the statements that were endorsed or refuted in conversation, or simply not brought up at all. We used a coding rubric by which a mentioned statement was labeled as either strongly endorsed (+3), endorsed (+2), slightly endorsed (+1), not mentioned (0), slightly opposed (−1), opposed (−2), or strongly opposed (−3). For example, the phrase "Antibiotics can kill COVID-19" would be assigned a + 1, the phrase "I really think that antibiotics can kill COVID-19" would get a + 2, and the phrase "I really think that antibiotics can kill COVID-19 because I've read studies that say it." a + 3. Conversely, the coding scheme was the mirror opposite for the opposing statements. For each participant we accounted for both their own input (i.e., self-endorsement, coded from −3 to +3) as well as their conversational partner's input (i.e., partner-endorsement, coded from −3 to +3) for each statement. Therefore, at the dyadic-level, conversational endorsement can fluctuate in the interval − 6 and + 6, which corresponds to the sum of conversational endorsement scores of the two conversational partners. Ten percent of the data were double coded for reliability (Cohen κ >0.88), and all disagreements were resolved through discussion between coders.

3 | RESULTS

3.1 | Low versus high epistemic conditions

We first tested the hypothesis that participants in the high epistemic condition would increase more in knowledge (i.e., by increasing their belief in accurate information and decreasing their beliefs in inaccurate information) compared to those in the low epistemic condition. To investigate, we ran a repeated measures ANOVA nested by conversational dyads to account for the participants' interactions in the conversational phase. We included belief change from pre-test to post-test as the dependent variable, epistemic condition (low and

TABLE 1 Definitions and illustrative figures of the dependent variables

MEASURE/DEFINITION	FIGURES
BELIEF A belief refers to the level of endorsement of a statement. Beliefs here refers to any of the 22 initial statements measured (i.e., 9 accurate, 9 inaccurate, and 4 conspiratorial).	
BELIEF CHANGE Belief change refers to participants' statement endorsement at post-test minus statement endorsement at pre-test. Belief change is computed for all 22 statements (i.e., 9 accurate, 9 inaccurate, and 4 conspiratorial).	
KNOWLEDGE Knowledge is operationalized as the difference between the endorsement of the 9 accurate statements and the 9 inaccurate statements (i.e., accurate minus inaccurate).	
KNOWLEDGE CHANGE Knowledge change represents the difference between knowledge at post-test and knowledge at pre-test (i.e., post minus pre).	
CONSPIRACY ENDORSEMENT Conspiracy endorsement refers to participants' endorsement of the 4 conspiratorial statements.	
CONVERSATIONAL ENDORSEMENT Conversational endorsement marks the statements that were endorsed or refuted in conversation, or simply not brought up at all	

high) as the between-subject variable, and statement type as the within-subject variable. We found a non-significant main effect of statement type F(2, 114) = 0.761, p = .470, ${\eta_p}^2$ = 0.013, a non-significant main effect of condition, F(1, 57) = 0.151, p = .699, ${\eta_p}^2$ = 0.003, and a non-significant interaction F(2, 114) = 0.015, p = .955, ${\eta_p}^2$ = 0.001 (Figure S1). Surprisingly, we did not find evidence that participants changed their beliefs differently in the two epistemic conditions.

Next, we wanted to investigate whether the epistemic manipulation impacted the conversational content. We first computed the percentage of statements (from a total of nine accurate, nine inaccurate, and four conspiracies), participants bring up in the conversation in each condition (Table 2).

Then, we ran a repeated measures ANOVA nested by conversational dyads, with the epistemic condition (low and high) as the between-subject variable and statement type as the within-subject variable. This time, the dependent variable was conversational endorsement. We found a significant main effect of statement type F(2, 114) = 20.58, p < .001, and ${\eta_p}^2$ = 0.265, not of condition, F(1, 57) = 1.00, p = .321, and ${\eta_p}^2$ = 0.017, and a significant interaction F(2, 114) = 7.87, p < .001, and ${\eta_p}^2$ = 0.121. Post-hoc analyses revealed that accurate statements were endorsed more in conversations in the high (M = 4.05, SD = 4.27) than in the low epistemic condition (M = 1.23, SD = 1.84), t(74) = 4.66, p < .001, and Cohen's d = 0.88, CI [1.67, 3.95]. However, inaccurate statements were not endorsed to different degrees in the high (M = −0.84, SD = 3.18) and low (M = −0.11, SD = 0.82) epistemic conditions (p = .090), and neither were conspiracies in the high (M = -0.48, SD = 2.17) and low (M = 0.22, SD = 3.62) epistemic conditions (p = .180). Therefore, we found that, as intended, participants endorsed more accurate statements in their conversations in the high epistemic condition (Figure 1).

TABLE 2 Percent of statements (from a total of 9 accurate, 9 inaccurate, 4 conspiracies), that are mentioned in the conversational phase in each condition

Condition	Accurate (%)	Inaccurate (%)	Conspiracy (%)
Low epistemic	12	5	31
High epistemic	29	13	19

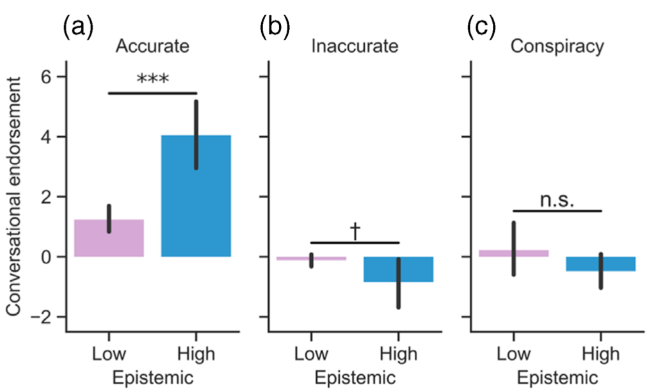


FIGURE 1 Conversational statement endorsement (joint self and partner) in the low (pink) and high (blue) epistemic conditions, split by statement type: Accurate (Panel a), inaccurate (Panel b), and conspiracy (Panel c). Note that because on the y axis we plot the *joint* endorsement, the interval is [−6, 6]. Error bars represent ±1 standard errors of the mean

3.2 | Belief change as a function of conversational interactions

To investigate our second hypothesis, that participants would align their beliefs with their conversational partner, we ran a linear mixed model with belief change as the dependent variable, partner conversational endorsement as the fixed effect, and by-participant, by-item, and by-dyad random intercepts. We added the by-dyad random intercepts to this model in order to treat the dyad as a unit of analysis, given that the participants' conversations create dependencies between pairs of participants who interact (Gałecki & Burzykowski, 2013). We found that indeed, the partners' conversational endorsement triggered the participants' belief change (β = 0.25, SE = 0.06, t[2402] = 4.00, and p < .001). This relationship remained significant (β = 0.22, SE = 0.06, t[2545] = 3.33, and p < .001) even when controlling to their participants' own conversational endorsement, by including self-conversational endorsement as another fixed effect in the model. Therefore, participants were sensitive to their conversational partners' endorsement of the statements, and changed their beliefs accordingly, such that the more their partner expressed disagreement with a statement in conversation the more the participant decreased their endorsement of that statement, and the more their partner expressed agreement with a statement in conversation, the more the participant increased their endorsement of that statement (Figure 2a). This effect did not interact significantly with the Epistemic Condition (see Supplementary Materials).

Furthermore, to uncover which beliefs were most susceptible to change, we split the 22 statements into three categories for each participant, according to their pre-test ratings, as: low endorsement (lowest-rated seven statements), moderate endorsement (middle eight statements), and high endorsement (highest seven statements). We then ran a linear mixed model with belief change as the dependent variable, partner conversational endorsement and type (low, mod, and high) as fixed effects, with by-participant, by-dyad, and by-item random intercepts. We found that partner conversational endorsement significantly triggered belief change for the initially moderately endorsed statements (β = 0.60, SE = 0.09, t[2578] = 6.35, and p < .001), but not for the initially low (β = 0.19, SE = 0.12, t[2582] = 1.51, and p = .133) or high (β = −0.19, SE = 0.11, t[2415] = −1.69, and p = .090) endorsed statements. Therefore, as hypothesized, the participants' sensitivity to their conversational partners' statement endorsement was driven by the beliefs they initially moderately endorsed (Figure 2b).

Lastly, to further explore which statements were most susceptible to change, we split the 22 statements by their actual accuracy, into

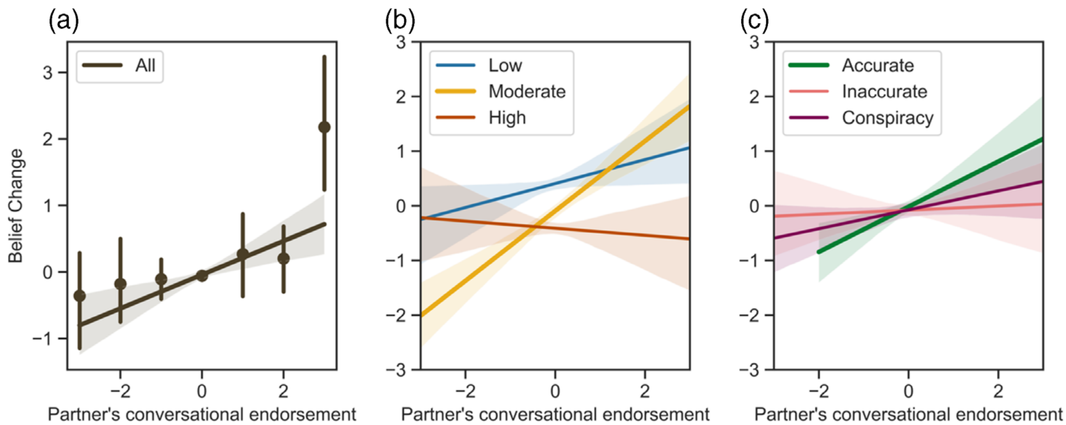


FIGURE 2 Belief update (self) as a function of the conversational partner's endorsement as conveyed in the conversational interaction, for all statements (Panel a), for the statements split into low (blue), moderate (yellow), and high (orange) endorsed statements at pre-test (Panel b), and for statements split into accurate (green), inaccurate (red), and conspiracy (purple) statements. Error bars represent 95% bootstrapped confidence intervals on the means

TABLE 3 Linear mixed model predicting knowledge at pre-test

	β	SE	Df	t	p	
(Intercept)	3.06	1.31	112	2.32	0.021	*
Trust in Trump	−0.13	0.06	112	−2.02	0.045	*
Trust in Fauci	0.21	0.08	112	2.64	0.009	**
COVID-19 threat	0.18	0.07	112	2.35	0.020	*
COVID-19 anxiety	−0.02	0.08	112	−0.27	0.784	
Dynamic anxiety	−0.11	0.13	112	−0.85	0.394	
PANAS positive	−0.31	0.20	112	−1.54	0.125	
PANAS negative	−0.35	0.24	112	−1.45	0.149	
News media	−0.04	0.03	112	−1.34	0.182	
Social media	−0.01	0.02	112	−0.43	0.662	
Age	0.02	0.01	112	1.77	0.077	
Education	0.03	0.17	112	−0.20	0.837	
Gender (F)	0.05	0.33	112	0.17	0.858	
Political orientation (D)	−0.01	0.41	112	−0.02	0.981	
Political orientation (R)	−0.16	0.55	112	−0.30	0.760	

accurate (nine statements), inaccurate (nine statements), and conspiracy (four statements). To investigate whether item type as a function of partner conversational endorsement rendered any differences in belief change, we ran a linear mixed model, with belief change as the dependent variable, partner conversational endorsement and type (accurate, inaccurate, conspiracy) as fixed effects, and by-participant, by-dyad, and by-item random intercepts. We found that partner conversational endorsement significantly triggered belief change for the accurate statements ($\beta = 0.42$, SE $= 0.09$, $t[1862] = 4.39$, and $p < .001$), but not for the inaccurate ($\beta = 0.04$, SE $= 0.12$, $t[2581] = 0.31$, and $p = .752$) or the conspiracy statements ($\beta = 0.19$, SE $= 0.11$, $t[2588] = 1.70$, and $p = .088$). Therefore, participants' sensitivity to their conversational partners' statement endorsement was driven by the accurate statements (Figure 2c).

3.3 | Exploratory analyses

In exploratory analyses, we first tested which variables predicted knowledge, and which predicted endorsing conspiracies. For knowledge (i.e., belief in accurate information minus belief in inaccurate information), we ran a linear model with knowledge at pre-test as the dependent variable; the fixed-effect variables we included were education level, age, gender, political orientation, trust in Trump, trust in Fauci, news media, social media, COVID-19 threat, COVID-19 anxiety, dynamic anxiety, PANAS positive emotions, and PANAS negative emotions. Of these, the significant predictors of knowledge were not trusting Trump, trusting Fauci, and COVID-19 threat (Table 3).

For conspiracy beliefs, we ran the same linear mixed model, except the dependent variable was conspiracy endorsement at pre-

TABLE 4 Linear mixed model predicting conspiracy at pre-test

	β	SE	Df	t	p	
(Intercept)	1.79	1.19	112	1.50	0.135	
Trust in Trump	0.21	0.05	112	3.68	<0.001	***
Trust in Fauci	−0.28	0.07	112	−3.81	<0.001	***
COVID-19 threat	0.09	0.06	112	1.34	0.180	
COVID-19 anxiety	0.02	0.07	112	0.33	0.740	
Dynamic anxiety	−0.07	0.12	112	−0.65	0.517	
PANAS positive	0.22	0.18	112	1.20	0.229	
PANAS negative	0.14	0.21	112	0.67	0.498	
News media	0.11	0.03	112	3.68	<0.001	***
Social media	0.04	0.02	112	2.01	0.046	*
Age	0.004	0.01	112	0.31	0.755	
Education	−0.11	0.16	112	−0.70	0.482	
Gender (F)	−0.43	0.29	112	−1.45	0.149	
Political orientation (D)	−0.77	0.37	112	−2.08	0.039	*
Political orientation (R)	0.01	0.49	112	0.02	0.982	

FIGURE 3 Knowledge (green) and conspiracy (purple) at pre-test, as a function of trust in trump and trust in Fauci

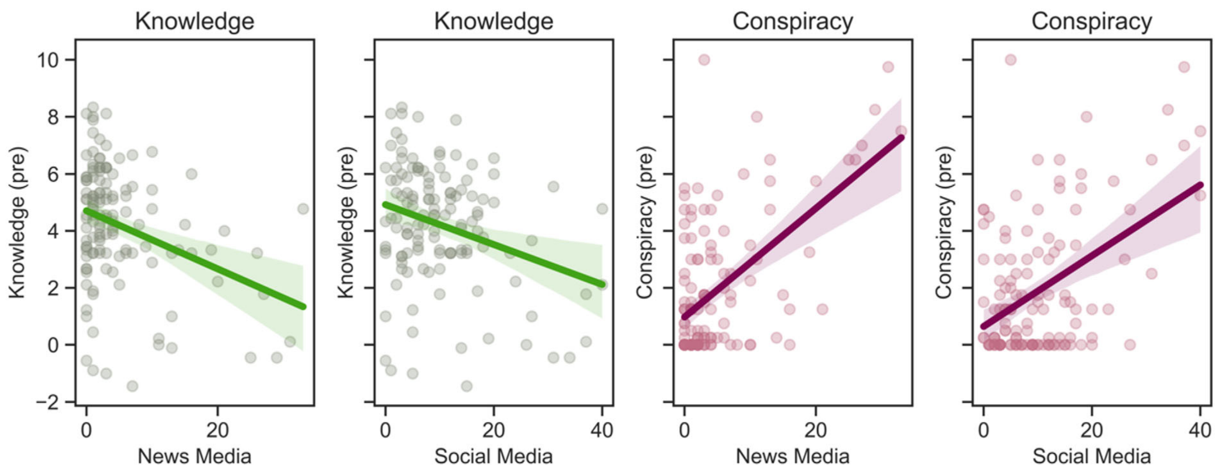


FIGURE 4 Knowledge (green) and conspiracy (purple) at pre-test, as a function of news media consumption and social media usage

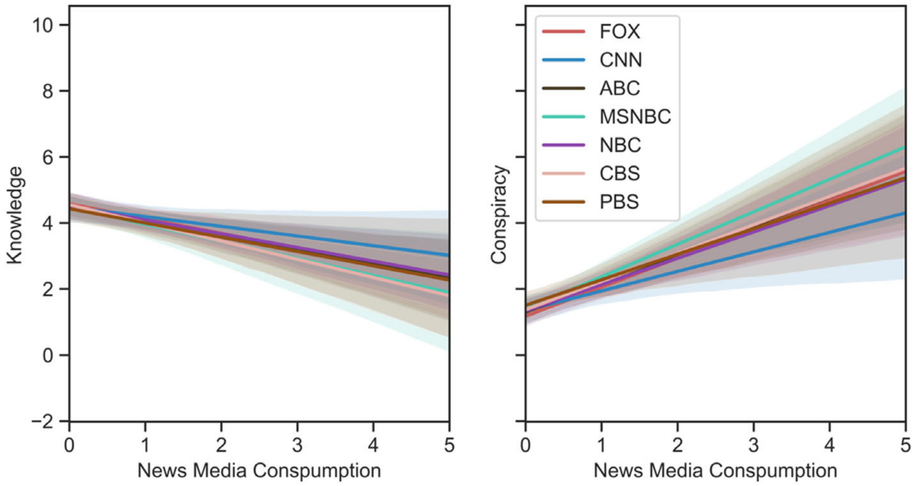


FIGURE 5 Knowledge (left) and conspiracy (right) at pre-test, as a function of news media consumption, by news networks

test. The significant predictors of believing conspiracies were trusting Trump, not trusting Fauci, news media consumption (i.e., more news media consumption was associated with stronger conspiracy endorsement), social media engagement (i.e., more social media consumption was associated with stronger conspiracy endorsement), and political orientation (i.e., alignment with the Democratic party was associated with weaker conspiracy endorsement) (Table 4).

To more intuitively display the significant predictors of knowledge and conspiracy beliefs in the two mixed models above, we plotted the regressions of trust in Trump and trust in Fauci (Figure 3) as well as news media consumption and social media participation (Figure 4), against knowledge and conspiracy belief.

Given the surprising result that news media consumption predicted conspiracy beliefs, we wanted to investigate whether this effect was driven by a particular news source, or whether it was a general effect of all news networks. We ran a linear mixed model with conspiracy endorsement at pre-test as the dependent variable, news media consumption and network (FOX, CNN, ABC, MSNBC, NBC, CBS, and PBS) as fixed effects, and by-participant random intercepts. We found no interaction of news consumption with news network ($p = .9$), suggesting that news consumption of any of the seven networks predicted conspiracy beliefs (Figure 5). For the sake of completion, even though not significant, we also plotted the news media consumption of each network as it predicted knowledge (Figure 5).

For additional ideological differences found in our sample, please refer to Supplementary Materials.

4 | DISCUSSION

In a high-risk environment, such as during an epidemic, people are exposed to a large amount of information, both accurate, inaccurate, and conspiratorial, which they typically discuss with each other in conversations. Here, we investigated the effectiveness of deploying a high epistemic accuracy manipulation on people's free-flowing communicative interactions regarding COVID-19, and their knowledge accumulation as a result of these interactions. In line to prior research showing the benefits of nudging epistemic accuracy, such as sharing less misinformation (Lewandowsky et al., 2012; Pennycook et al., 2021), we found that participants in the high versus low epistemic condition discussed more accurate information. However, in contrast to these prior studies, we found that the difference in conversational content did not lead to differences in how knowledgeable participants in the two conditions became as a result of conversations. This finding points to a higher resistance to this manipulation when it comes to changing one's beliefs compared to simply choosing what to discuss and propagate. Therefore, this study provides evidence for a possible boundary condition of these types of interventions.

We speculate that one reason the epistemic accuracy manipulation did not have the intended effect could be that while the belief change was computed for all the statements tested, only a small subset of them (16%) were on average discussed in each conversation (Figure S3). Talking about these statements did increase the participants' post-conversational endorsement, but they were too few to impact the entire knowledge score. This observation could open up interesting theoretical avenues. For instance, the size of the set of beliefs one measures can moderate the strength of the epistemic manipulation, such that when few beliefs are measured the epistemic accuracy effect is apparent, whereas when measuring a larger set, it is not.

We also show that, during the coronavirus pandemic, individuals talking to each other are sensitive to their conversational partners, by changing their beliefs regarding COVID-19 information according to their partners' conveyed beliefs. This influence is strongest for initially moderately held beliefs (compared to initially endorsed or opposed beliefs), and for accurate information (compared to inaccurate or conspiracy information), which is of note particularly from an intervention perspective. These findings extend prior research showing the impact of conversational interactions on memory (Cuc et al., 2007), and align with prior research showing individuals are susceptible to social norms (Cookson et al., 2021; Vlasceanu & Coman, 2021), and synchronize their beliefs after engaging in conversations with other participants in social networks (Vlasceanu et al., 2020; Vlasceanu & Coman, 2022).

Lastly, in exploratory analyses, we found that having COVID-19 knowledge is predicted by trusting Fauci, not trusting Trump, and feeling threatened by COVID-19. Conversely, endorsing conspiracies is predicted by trusting Trump, not trusting Fauci, news media consumption, social media usage, and political orientation. These findings, although in need of confirmation through subsequent replications, also align with prior work and have important implications in the current socio-political context. The interaction between ideology and conspiracy endorsement is consistent with prior instances in which Republicans endorsed conspiracy theories more than Democrats (Pasek et al., 2015), and with the general trend in the wider political literature of Republicans being more likely to believe conspiracies about democrats and vice versa (Hollander, 2018; Miller et al., 2016; Oliver & Wood, 2014; Radnitz & Underwood, 2017; Smallpage et al., 2017). These trends are applicable in the case of COVID-19, which was labeled a "hoax" by President Trump, and a "Democratic hoax" by Eric Trump. A surprising finding was that news media consumption positively predicted believing conspiracies regarding COVID-19, even when controlling for demographic variables such as age, gender, education, and political orientation. This effect was not driven by a particular news network, instead it was a general effect of news media consumption. This finding counters prior work suggesting that people consuming news media are less likely to believe conspiracies (Hollander, 2018; Stempel et al., 2007) and that people who are more knowledgeable about news media are also less likely to endorse conspiracy theories (Craft et al., 2017). Thus, clarifying the mechanism of this discrepancy would be a worthwhile future trajectory.

Several other research trajectories emerge from this work. For instance, an important aspect of belief change that was omitted here is source credibility (Chung et al., 2008; Slater & Rouner, 1996; Vlasceanu & Coman, 2022). This line of work would benefit from future investigations into how the source presenting information might influence the conversational content and belief change, and how this influence might be amplified or attenuated by conversations. Also, the future work could investigate whether revealing features of the conversational partner, such as their ideological orientation, might moderate the individuals' willingness to change their beliefs as a function of their conversations. The present work could also be extended from the dyadic level to the collective belief level (Vlasceanu et al., 2018; Vlasceanu & Coman, 2022) by investigating the effect of multiple conversations within communities on belief change. Critically, these dyadic-level influences (i.e., from speaker to listener) have been found to propagate in social networks (Coman et al., 2016; Vlasceanu et al., 2020). In line with the existing research, it is likely that the high perceived risk of infection might influence the propagation of information through social networks. Tracking information propagation in fully mapped social networks would be critically important, especially given the policymakers' interests in impacting communities at scale (Dovidio & Esses, 2007).

In conclusion, in a high-risk environment (i.e., during the COVID-19 pandemic), conversational interactions were a powerful avenue of social influence, conversations shaping the people's COVID-19 beliefs. Despite the conversations' significant impact on beliefs, an intervention aimed at eliciting conversations focused on accurate information did not successfully change the people's beliefs toward increased accuracy. These findings are especially relevant in the context of misinformation prevention, an undertaking of particular consequence during global instability.

AUTHOR CONTRIBUTIONS

Madalina Vlasceanu and Alin Coman developed the study concept and design. Testing and data collection and analyses were performed by Madalina Vlasceanu. Madalina Vlasceanu drafted the manuscript, and Alin Coman provided critical revisions. Both authors approved the final version of the manuscript for submission.

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CONFLICT OF INTEREST

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

Availability of data and materials: All data and materials can be found on our OSF page here: https://osf.io/sk4dt/

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SUPPORTING INFORMATION

Additional supporting information may be found in the online version of the article at the publisher's website.

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