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Misplaced trust: When trust in science fosters belief in pseudoscience and the benefits of critical evaluation☆

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ABSTRACT

At a time when pseudoscience threatens the survival of communities, understanding this vulnerability, and how to reduce it, is paramount. Four preregistered experiments ($N = 532$, $N = 472$, $N = 605$, $N = 382$) with online U.S. samples introduced false claims concerning a (fictional) virus created as a bioweapon, mirroring conspiracy theories about COVID-19, and carcinogenic effects of GMOs (Genetically Modified Organisms). We identify two critical determinants of vulnerability to pseudoscience. First, participants who trust science are more likely to believe and disseminate false claims that contain scientific references than false claims that do not. Second, reminding participants of the value of critical evaluation reduces belief in false claims, whereas reminders of the value of trusting science do not. We conclude that trust in science, although desirable in many ways, makes people vulnerable to pseudoscience. These findings have implications for science broadly and the application of psychological science to curbing misinformation during the COVID-19 pandemic.

The impact of science depends on people accepting scientific knowledge, which in turn requires trust: A willingness to accept vulnerability to others' behavior based on positive expectations (Rousseau, Sitkin, Burt, & Camerer, 1998). Whether the goal is to encourage communities to follow COVID-19 mitigation measures or policy makers to reduce carbon emissions, scientific information will promote these goals only if people believe it. In this paper, we asked whether the trust that leads people to belief in scientific information may become a liability when the public is exposed to seemingly scientific but false contents and labels (i.e., pseudoscience). This question is important to all areas of psychology as well as other sciences and the application of psychological knowledge to curbing what has been described as an "infodemic" of misinformation (World Health Organization, 2020).

The COVID-19 pandemic and the politicization of health-prevention measures in the U.S. highlight the importance of accepting and trusting science (Most Americans Say They Regularly Wore a Mask in Stores in Past Month | Pew Research Center, 2021.; Oreskes, 2019). Some segments of the public continue to cast doubt on the severity of climate change or the COVID-19 pandemic, whereas others go as far as denying them altogether (Richard & Medeiros, 2020; Ruths, 2019). At a time when misconceptions and denial have potentially disastrous social and health outcomes (Hornsey, Harris, & Fielding, 2018b), it is only natural to see frequent calls to trust science (i.e., to be willing to believe in and accept the judgment and actions of scientists and the field of science, Crease, 2004). For example, in relation to the White House's handling of the current COVID-19 pandemic, Nancy Pelosi recently declared, "These decisions may have to be made locally because of the rate of infection in certain areas, but they have to be made *scientifically*" (CNSNews, 2021). This deference to scientific consensus highlights that the U.S. must not ignore the SARS-CoV-2 science.

Some *broad* calls for trust in science, however, go beyond specific issues by attempting to promote a broad confidence in the body of scientific knowledge and scientists. For example, during the 2016 Democratic National Convention, Hillary Clinton said, "I believe in science!" (Hillary Clinton Declares, "I Believe in Science" - Scientific American, 2021). Attendees of the convention applauded because trust in science is necessary for the functioning of society and perhaps because her speech ran contrast to the outright denial of scientific consensus about climate change (Arimoto & Sato, 2012). Similarly, an entire line of products enables people to express their trust of science with t-shirts, bumper stickers, and other products to reflect membership in a social group that trusts science (Science Stores | Teespring, *2021*).

Indeed, trusting science has important benefits for society and individuals. Trust in science strengthens public support and funding for

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science, which in turn increases the probability of scientific discoveries and societal wellbeing (Muñoz, Moreno, & Luján, 2012; National Science Foundation, 2016). Secular individuals may also use trust in science as a way to buffer anxiety in the way that religious individuals use religion (Farias, Newheiser, Kahane, & de Toledo, 2013). Unfortunately, however, a broad trust in science involves a confidence that could be displaced from science onto misinformation invoking scientific credentials. Pseudoscientific claims can come from people carrying, or misrepresented as carrying, scientific credentials, or from communities (Hoffman et al., 2019) or politicians who cite questionable or retracted scientific studies. One example is politicians who perhaps rely on a now-retracted report from *The Lancet* (Mehra, Desai, Ruschitzka, & Patel, 2020) and advocate the use of hydroxichloroquine to treat COVID-19, despite potential harm to patients and lack of evidence of positive effects (Dejong & Wachter, 2020).

1. The dangers of misplaced trust

Although crucial for cooperation with authorities (Tyler & Blader, 2003), trust produces negative outcomes when people stop critically evaluating information. For example, blindly accepting all advice from healthcare providers without any critical evaluation may harm patients' health (Peters & Bilton, 2018). In intergroup relations, positive contact may create false expectations that reduce necessary collective action for social change (Saguy, Tausch, Dovidio, & Pratto, 2009). In this research, we hypothesized that trust could also be misplaced when an audience encounters pseudoscience. Such dangerous pseudoscience could include theories originally considered scientific, such as biological theories of racial hierarchy (Kendi, 2016). Other forms propose simplistic solutions to complex problems, such as reports of cures for the SARS-CoV-2 virus (These are false cures and fake preventative measures against coronavirus. Help fact-checkers spread the word – Poynter, *2021*). Yet others comprise facts that are taken out of context to obfuscate support for policies to reduce carbon emissions (Joshi, 2014). These pseudoscientific claims are of course difficult to debunk because they resonate with true, scientific mental models (Chan, Jones, Hall Jamieson, & Albarracín, 2017) and often take advantage of some misguided intuition (Holyoak & Thagard, 1997).

Pseudoscience claiming conspiracy is particularly problematic because it preempts the possibility of invalidation. The central claim is that any disconfirming information has been falsified by ill-intended agents, typically a powerful group (Hornsey, Harris, & Fielding, 2018a). Conspiracy claims become a public health threat (Kalichman, 2009) when they concern HIV (Human Immunodeficiency Virus) being the result of a secret plot to control ethnic minority populations (Bogart & Thorburn, 2005) or when they characterize vaccines as a plot of *Big Pharma* (Hornsey et al., 2018a), or SARS-CoV-2 as either a bioweapon created by the Chinese government or an exaggeration of CDC (Centers for Disease Control) to harm the presidency of Donald Trump (Hall Jamieson & Albarracín, 2020). Early in 2020, nearly one-third of U.S. adults endorsed a conspiracy theory about the novel coronavirus having been created intentionally in a lab (Hall Jamieson & Albarracín, 2020; Uscinski et al., 2020).

2. Critical evaluation of evidence

Educators and scholars have long advocated promoting critical evaluation of scientific claims for making health and political decisions (Brickman et al., 2012). In order to process complex information about scientific topics, one must have the knowledge and skills to scrutinize (for evidence on the impact of knowledge on elaborative information processing, see Wood, 2000; for the general impact of ability to process information on information processing, see Chaiken, 1980). One way to consider this form of processing in the education literature is in the form of methodological literacy (Gormally, Brickman, & Lutz, 2012). This type of scientific literacy –methodological literacy– involves the critical evaluation of claims (Brickman et al., 2012; Sharon & Baram-Tsabari, 2020). Another way of conceptualizing critical evaluation is as cognitive style. People who make more errors in judgments about probability are more likely to believe in paranormal theories (Rogers, Fisk, & Lowrie, 2018). People who have less rational, less open-minded (e.g., considering alternatives and multiple possibilities) and more intuitive thinking styles (e.g., quick reactions, prone to affective judgments) are also more likely to believe in conspiracy theories (Swami, Voracek, Stieger, Tran, & Furnham, 2014), whereas people who score higher on a cognitive reflection test and on science curiosity are more able or motivated to discern fake from accurate news (Kahan, Landrum, Carpenter, Helft, & Hall Jamieson, 2017; Motta, Chapman, Haglin, & Kahan, 2019; Pennycook & Rand, 2019).

Critical evaluation may also be promoted situationally. Deliberation reduces susceptibility by allowing participants to rethink their initial intuition and correct it after their initial failure to reject it (Bago, Rand, & Pennycook, 2020). Furthermore, a meta-analysis of debunking efforts identified strategies to make an audience active in counterarguing as the most important moderator of debunking efforts (Chan et al., 2017). In this regard, psychologists have long advocated the notion of *mindsets*, a set of mental routines activated in a given situation (Albarracin, 2020; Oettingen & Gollwitzer, 2000; Taylor & Gollwitzer, 1995; Wyer Jr., 2019; Wyer Jr. et al., 2012; Xu & Wyer Jr., 2008). For example, recalling or imagining instances of past activity leads people to reestablish those action goals and apply them to present information (Jiang & Albarracín, 2019). Recalling an instance in which critical evaluation was useful may also reinstate those procedures and lead people to critically evaluate pseudoscience. Although evidence that critical evaluation reduces susceptibility to misinformation contradicts calls for trusting science broadly as a remedy to misinformation, a critical evaluation approach to reducing misinformation has never been evaluated vis-à-vis a trust of science approach to reducing misinformation.

Although the literature suggests that methodological literacy should have protective benefits against misinformation, there is mixed support for the broader hypothesis that knowledge or numeracy should protect against misinformation. Although lack of knowledge and skills have been linked to susceptibility to misinformation, values and convictions have long shaped how the public responds to scientific information (Scheufele & Krause, 2014). When faced with issues of political controversy such as climate change, people who have greater numerical abilities and more knowledge of scientific facts may cling more strongly to views that align with their political ideology rather than views that align with science (Kahan et al., 2012). However, other research has cast doubt on the generalizability of this finding, observing that cognitive sophistication does not exacerbate the effects of political ideology on beliefs (Tappin, Pennycook, & Rand, 2020).

3. The present research

The goal of the current research, which involved four pre-registered experiments, was to examine the impact of trust in science and critical evaluation on belief in pseudoscience by crossing these factors with the presence or absence of scientific references. In Experiments 1–3, we operationalized critical evaluation as methodological literacy, which we measured. In Experiment 4, we operationalized critical evaluation as a mindset, which we manipulated. Generally, we expected trust in science to increase belief in and dissemination of misinformation containing scientific contents but to decrease belief in and dissemination of information without scientific contents, operationalizing scientific content as quoting scientists as a source and referring to studies they conducted. We expected critical evaluation to decrease belief in misinformation across the board. To test our hypotheses, we instructed participants to read an article containing false claims concerning a virus created as a bioweapon, or in the case of Experiments 3–4, the effects of GMOs on tumors. Depending on experimental condition, however, the claims contained references to either (a) scientific concepts and scientists who claimed to have conducted research on the virus or GMOs (scientific content), or (b) lay descriptions of the same issues from activist sources (no scientific content). Generally, we expected the scientific contents to lead to stronger beliefs in and dissemination of the materials. More critical to our hypotheses, however, if trust in science makes people vulnerable to pseudoscience, trust in science should interact with scientific content, fostering more belief and dissemination when the information had scientific content than when it did not. We also assessed the effects of methodological literacy in all cases.

Experiment 4 was intended as a causal test of the hypothesis that critical evaluation reduces susceptibility. Specifically, we induced a critical evaluation mindset and compared it with a trust in science mindset and a control mindset. We predicted that mindset would interact with scientific content: when participants read the article with scientific content, the trusting science mindset may lead to the strongest level of belief, followed by the control mindset, followed by the critical evaluation mindset. In contrast, when participants read the article without scientific content, the critical evaluation mindset may lead to the strongest level of belief, followed by the control mindset, followed by the trusting science mindset. As preregistered, our experiments involved a complex model and accounted for all possible interactions. Models were evaluated via cross-validation (de Rooij & Weeda, 2020) to select best fitting models. Across studies, we disclose all conditions, variables, and exclusions, with descriptions in the main text and complete text of all manipulations and variables in the Supplemental File. Across studies, we report sensitivity analyses after hypothesis testing for each outcome.

4. Preregistered experiment 1: trust in science and methodological literacy and the impact of medical pseudo-science

4.1. Methods

4.1.1. Participants and design

We collected data from 604 participants (excluding 31 participants who began but did not complete the study) within the U.S. via Amazon's Mechanical Turk (MTurk; Buhrmester, Talaifar, & Gosling, 2018). We excluded the data of 88 participants (12% of those who finished) because they did not pass a simple attention check asking them to write "yes" in a blank field. The remaining 532 participants included 198 who identified as female and 334 who identified as male, ages ranging from 18 to 76 years (omitting data of participants who wrote unlikely values), M of age = 37.66 years, SD = 11.92 years. On a scale to assess political ideology, from "Strong liberal" (1) to "Strong Conservative" (5), the average level of political ideology was 3.04 (closest to "True moderate"), SD = 1.34. On a scale to assess formal education, from "Elementary School" (1) to "Doctoral degree" (6), the average level of education reported was 3.94 (closest to 4, "Bachelor's degree"), SD = 0.86. Of those who reported race and ethnicity, 65.98% identified as White, 14.10% identified as African American, 10.34% identified as Hispanic, 5.26% identified as Asian, 3.01% identified as Native American, 0.02% identified as Pacific Islander, and 1.32% identified as "Other". We based our sample size on a priori power analyses described in the preregistration (link available in methods section of each experiment) conducted with GPower (Erdfelder, FAul, Buchner, & Lang, 2009). For Experiments 1–3, we specified a Cohen's f of 0.15, for an ANCOVA with two groups. Although this analysis suggested we needed 489 participants, we collected additional participants with an expectation that some would not pass a simple attention check and thus not be included in analyses.

The experimental design was a 2 (content: scientific vs. not scientific) x continuous (measure of trust in science) x continuous (measure of methodological literacy) design. The preregistration of this experiment appears in Open Science Framework (OSF; Link for Experiment 1)[1] with author information hidden for review. Data for Experiment 1 was collected between April 30th and May 7th, 2020.

5. Procedure, materials, and measures

Upon consenting to the survey, participants were randomly assigned to either the scientific content condition (N = 261) or the non-scientific content condition (N = 271). In both conditions, participants learned about the "Valza Virus" with an ostensible expert claiming that the virus was created in a government lab and covered-up (a key feature of conspiracy theories). In the scientific content condition, the article cited scientists at prominent universities, describing how studies conducted in their laboratory proved that the virus was created in a laboratory and that the U.S. government concealed their role in creating the virus. In the non-scientific content condition, the article cited activists as the expert source and quoted one of the activists. The style of the articles (see Supplement Part G) was informal, imitating websites and postings from subscribers of the theories.

Upon finishing the article, participants were instructed to reflect upon it and asked several questions about their perceptions of the article presentation, to support the cover story that the research involved comprehension and distract participants to the true purpose of the experiment. Following these questions, we measured (a) *belief* in the article through six items used in pilot studies, (b) the behavior of *dissemination* of the article consistent with a measure used in pilot studies, (c) *trust in science* using eight items partially derived from a scale validated in past research (Nadelson et al., 2014) and partially from items we created and tested with pilot studies, and (d) *methodological literacy* using a mix of items used from past research and items that we created and pre-piloted. As described in Supplement Part B, the shortened scale including our own items correlates strongly, r = 0.81, with the full scale validated in past research (Nadelson et al., 2014). We measured dissemination before belief to prevent leading answers.

5.1. Belief (α = 0.90, M = 3.58, SD = 0.93)

Participants were instructed to state their agreement between "Strongly Disagree" (1) to "Strongly agree" (5), that the article was "strong", "probably true", "credible", "convincing", "plausible", and contained "meaningful information".

5.2. Dissemination

Participants were instructed that the researchers conducting the study were taking a tally of participants who support using the article as part of a class: "Before we continue, the researcher in charge of this study also teaches an online current-events (contemporary news, media) class. We would like to have a ballot as to whether different news articles might be of interest or value for such a class. Please vote on whether or not this article should be emailed out to all of the students as part of their participation in the class." Of the 532 participants, 403 (76%) voted to share the article and 129 (24%) voted not to share.

5.3. Trust in science (α = 0.81, M = 3.25, SD = 0.76)

Participants were instructed to state their agreement that *Scientists usually act in a truthful manner and rarely forge results*, *scientists intentionally keep their work secret* (reverse), *the bible provides a stronger basis for understanding the world than science does* (reverse), *scientific theories are trustworthy*, *scientific theories are often taken too seriously* (reverse),

[1] The full hyperlink can be copied and pasted into a browser: https://osf.io/4frvp/?view_only=efae2805729a4a569c34c3a0e684d2c8

scientific theories do not matter very much because they can be wrong (reverse), *science is a trustworthy way to better understand the world we live in*, and *when scientists change their mind about a scientific idea it diminishes my trust in their work* (reverse). Responses were provided on scales from "Strongly disagree" (1) to "Strongly agree" (5).

5.4. Methodological literacy ($M = 3.67$, $SD = 2.01$)

Participants were asked eight multiple choice questions to assess their understanding of scientific methodology. Supplementary materials include all questions. As an example, participants read the claim that *Creators of the Shake Weight, a moving dumbbell, claim that their product can produce "incredible strength!"*. and then selected which statement offered the best evidence for the claim. Specifically, the four options were (a) "Survey data indicates that on average, users of the Shake Weight report working out with the product 6 days per week, whereas users of standard dumbbells report working out 3 days per week," (b) "Compared to a resting state, users of the Shake Weight had a 300% increase in blood flow to their muscles when using the product," (c) "Survey data indicates that users of the Shake Weight reported significantly greater muscle tone compared to users of standard dumbbells," and (d) "Compared to users of standard dumbbells, users of the Shake Weight were able to lift weights that were significantly heavier at the end of an 8-week trial." The correct answer was (d). As another example, participants read the claim "In an experiment, the independent variable is the one thing you". The choices were (a) "change/manipulate", (b) "keep the same/do not manipulate," (c) "investigate," and (d) "avoid," and the correct answer was (a). For each wrong answer, participants were assigned a value of 0, and for each correct answer, they were assigned a value of 1. The composite was the sum of correct responses, thus a maximum raw value of eight and a minimum of 0. Because knowledge measures cannot be properly analyzed with internal consistency items (Zanon, Hutz, Yoo, & Hambleton, 2016), to test reliability, we used item response theory with a Rasch model. We obtained goodness of fit statistics using the eRm package in *R*, collapsed deviance = 171.16, $df = 56$, $p < .001$, *Pearson* $R^2 = 0.25$, area under *ROC* = 0.79 (Mair, Hatzinger, & Maier, 2020).

5.5. Debriefing

At the end of the study, participants answered the question: "In your opinion, what was the purpose of this study?" These responses were coded blind to the condition for whether participants' responses (a) mentioned the possibility of scientific content increasing belief or dissemination, (b) mentioned that trust in science would correlate with more or less belief in and dissemination of information, (c) mentioned that knowledge about science or methodological literacy would correlate with belief in and dissemination of information, and (d) mentioned that our key hypothesis that people who trust science would be more likely to believe in or disseminate information containing scientific content. Responses were coded as having guessed the purpose if their response fit into one or more of these categories.

6. Results

6.1. Ruling out demand effects

To examine the possibility of demand effects, we analyzed the responses to the debriefing question. Four participants guessed that the purpose involved testing whether methodological literacy was related to belief, and two participants guessed that the purpose was testing if people believe more in stories with than without scientific content. Although these guesses did not accurately reflect our key hypothesis about the interaction between trust in science and scientific content, they deserved attention. However, analyses in Supplement Part E demonstrated that excluding these participants did not result in substantively different results from the final models presented in the main text.

6.2. Main analyses

We tested the hypothesis that scientific content would lead to stronger belief and more dissemination among participants with higher trust in science. As pre-registered, we conducted analyses by entering a dummy variable coded as '1' for the scientific content condition and '0' for the non-scientific content condition. Trust in science was introduced as a covariate along with a two-way interaction between trust in science and the scientific content dummy variable. We conducted these analyses controlling and not controlling for methodological literacy using ANCOVAs (Analyses of Covariance) for *belief* and logistic regression for the outcome of dissemination ('1' for 'yes' and '0' for 'no'). Trust in science and methodological literacy were transformed to *z*-scores for analyses. Using the *R* package xvalglms (de Rooij & Weeda, 2020), we first assessed models using cross-validation (de Rooij & Weeda, 2020) to find the best fitting one among models with all or fewer possible combinations of variables, and an intercept-only model. The model fit plots appear in Fig. 1 of Supplement Part C and showed that the best models for both belief and dissemination included scientific content, trust, and methodological literacy as main effects as well as the interaction between scientific content and trust. The coefficients for the full and best fitting models to predict belief and dissemination appear in Tables 1 and 2 of this paper. Interactions were decomposed by relying on one standard deviation above the mean of trust in science for "high" levels of trust, and one standard deviation below the mean of trust in science for "low" levels of trust. The best-fitting model according to cross-validation (de Rooij & Weeda, 2020) was the model which included all main effects and the two-way interaction between trust in science and scientific content, but not interactions with methodological literacy. Table 3 presents predicted values corresponding to our key interaction between content and trust in science. Supplement Part C explains the model comparison procedures in more detail.

6.3. Belief

The critical hypothesis was that vulnerability to pseudoscientific content would be greater among participants with higher (vs. lower) trust in science. Consistent with this possibility, belief was a function of the interaction between scientific content and trust in science (see Table 1). Among participants with higher levels of trust in science (one standard deviation above the mean), reading scientific content led to stronger belief than reading non-scientific content, $F(1, 527) = 79.00$, $p < .001$, $\eta p^2 = 0.07$. In contrast, among participants with lower levels of trust in science (one standard deviation below the mean), the presence or absence of scientific content had no impact, $F(1, 527) = 0.79$, $p = .375$, $\eta p^2 = 0.07$.

Also as predicted, participants in the scientific content condition ($M = 3.79$, $SD = 0.73$) had stronger beliefs that the non-scientific content condition ($M = 3.38$, $SD = 1.06$), as a main effect. Furthermore, trust in science and methodological literacy were each associated with lower beliefs. See Table 3 for estimated levels of belief across scientific and non-scientific conditions for participants with low and high levels of trust in science.

To assess sensitivity of effects on belief, we used G*Power (Erdfelder et al., 2009), selecting the sensitivity analysis option with ANCOVA (F test family), inputting 0.80 for power, with 532 participants, one within degree of freedom, with alpha at 0.05, two groups, and three covariates. The sensitivity analysis showed that the required *Cohen's f* would be 0.12, compared to the actual *Cohen's f* of 0.27 for the main effect of scientific content and 0.30 for the interaction.

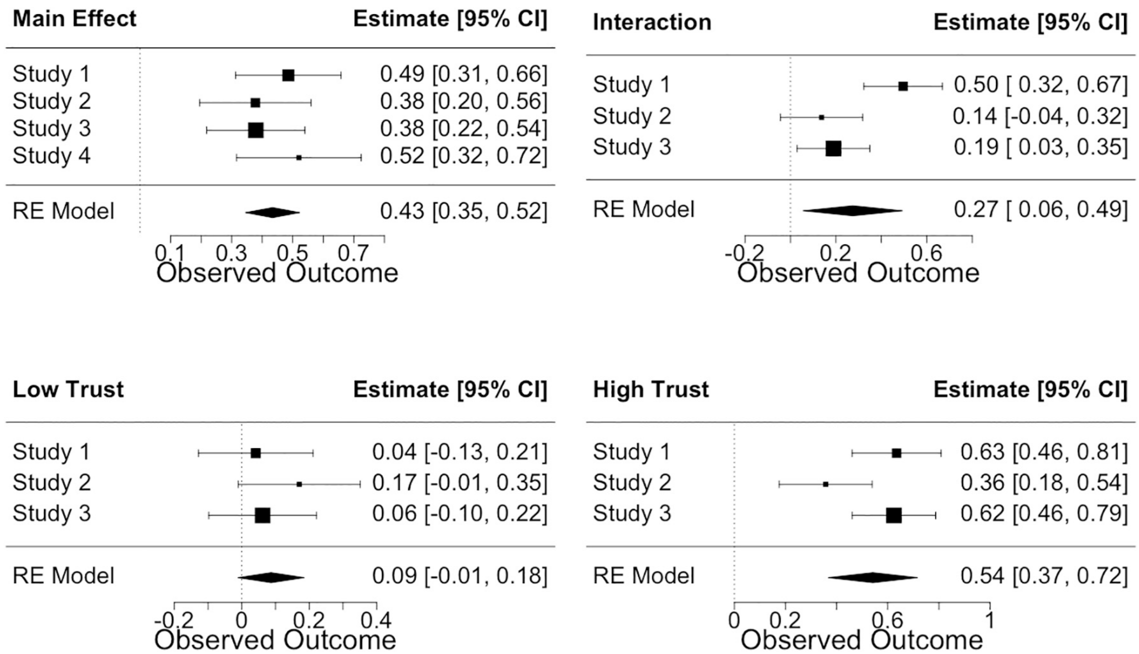

Fig. 1. Forest plots of scientific content and its interaction with trust in science predicting belief. Using Hedge's *g* to estimate effect size, the plots above show effect sizes for each study with 95% confidence intervals the right-hand side and the estimated average effect in a random effects model at the bottom. This includes plots show the main effect of scientific content on belief across Experiments 1–4 (top left), the estimated two-way interaction between scientific content and trust in science across Experiments 1–3 (top right), the estimated main effect of scientific content for those with low trust in science across Experiments 1–3 (bottom left), and the estimated main effect of scientific content for those with high trust in science across Experiments 1–3 (bottom right).

Table 1
Results of full and final Anova models with betas of multiple regression models predicting belief across Experiments 1–3.

Experiment 1	*B*	*F*	*p*	η_p^2	*B*	*F*	*p*	η_p^2
Intercept	3.41	4145.15	<0.001		3.40	5989.33	<0.001	
Scientific Content	0.44	31.44	<0.001	0.07	0.39	32.30	<0.001	0.07
Trust	-0.48	71.63	<0.001	0.18	-0.50	97.86	<0.001	0.18
Literacy	-0.21	14.23	<0.001	0.03	-0.18	21.44	<0.001	0.03
Scientific Content x Trust	0.49	32.80	<0.001	0.08	0.48	47.88	<0.001	0.08
Scientific Content x Literacy	0.05	0.46	0.496	0				
Trust x Literacy	-0.01	2.12	0.146	0				
Scientific Content x Trust x Literacy	-0.09	1.43	0.232	0				
Experiment 2								
Intercept	3.10	4722.95	<0.001		3.08	2228.84	<0.001	
Scientific Content	0.39	16.88	<0.001	0.05	0.44	23.14	<0.001	0.04
Trust	-0.21	8.74	0.003	0.05	-0.24	12.11	0.001	0.05
Literacy	-0.33	22.21	<0.001	0.06	-0.25	27.33	<0.001	0.06
Scientific Content x Trust	0.14	2.22	0.137	0.01	0.21	5.10	0.024	0.01
Scientific Content x Literacy	0.14	2.11	0.147	0.01				
Trust x Literacy	-0.09	1.72	0.190	0				
Scientific Content x Trust x Literacy	0.14	2.19	0.139	0				
Experiment 3	*B*	*F*	*p*	η_p^2	*B*	*F*	*p*	η_p^2
Intercept	3.37	3600.55	<0.001		3.37	3600.55	<0.001	
Scientific Content	0.40	21.71	<0.001	0.05	0.40	21.71	<0.001	0.05
Trust	-0.40	40.65	<0.001	0.17	-0.40	40.74	<0.001	0.17
Literacy	-0.25	17.25	<0.001	0.02	-0.25	17.25	<0.001	0.02
Scientific Content x Trust	0.21	5.42	0.020	0.04	0.21	5.42	0.020	0.04
Scientific Content x Literacy	0.20	5.13	0.024	0.01	0.20	5.13	0.024	0.01
Trust x Literacy	−0.15	6.31	0.012	0.01	-0.15	6.31	0.012	0.01
Scientific Content x Trust x Literacy	0.09	1.29	0.257	0	0.09	1.29	0.257	0

Terms are abbreviated across rows: "Trust" represents trust in science, "Literacy" represents methodological literacy, and x denotes an interaction between variables. For Experiment 1, the within degrees of freedom are 524 for the full model and 527 for the final model. For Experiment 2, the within degrees of freedom are 456 for the full model and 459 for the final model.

6.4. Dissemination

A significant two-way interaction also supported our hypothesis that the effect of scientific content on dissemination would differ across levels of trust in science (see Table 2). For participants with higher trust in science, scientific content increased the probability of dissemination by 0.69, $b(\text{logit}) = 0.78$, $SE = 0.29$, $z = 2.73$, $p = .006$. In contrast, for participants with lower trust in science, scientific content had no effect, $b(\text{logit}) = -0.19$, $SE = 0.41$, $z = -0.47$, $p = .637$. Also as predicted, trust in science and methodological literacy were each negatively associated with dissemination. In contrast to our hypotheses, however, there was no main effect of scientific content. See Table 3 for estimated

Table 2
Results of full (left hand side) and final (right hand side) models predicting dissemination across Experiments 1–3.

	B	*SE*	*p*	Prob.	*B*	*SE*	*p*	Prob.
Intercept	1.39	0.21	<0.001	0.80	1.38	0.18	<0.001	0.80
Scientific Content	0.29	0.29	0.317	0.57	0.29	0.26	0.255	0.57
Trust	−1.27	0.21	<0.001	0.22	−1.00	0.17	<0.001	0.27
Literacy	−1.08	0.24	<0.001	0.25	−0.79	0.14	<0.001	0.31
Scientific Content x Trust	0.78	0.31	0.011	0.69	0.49	0.24	0.043	0.62
Scientific Content x Literacy	0.28	0.32	0.384	0.57				
Trust x Literacy	0.57	0.19	0.003	0.64				
Scientific Content x Trust x Literacy	−0.61	0.28	0.032	0.35				
Experiment 2								
Intercept	−0.03	0.14	0.815	0.49	-0.03	0.14	0.815	0.49
Scientific Content	0.38	0.20	0.058	0.59	0.41	0.19	0.030	0.60
Trust	−0.14	0.15	0.354	0.47				
Literacy	−0.37	0.15	0.012	0.41	-0.40	0.10	<0.001	0.40
Scientific Content x Trust	0.11	0.20	0.587	0.53				
Scientific Content x Literacy	−0.06	0.21	0.790	0.49				
Trust x Literacy	0.00	0.15	0.988	0.50				
Scientific Content x Trust x Literacy	0.10	0.21	0.627	0.53				
Experiment 3								
Intercept	1.26	0.13	<0.001	0.78	1.33	0.12	<0.001	0.79
Scientific Content	−0.30	0.13	0.020	0.43	-0.33	0.12	0.005	0.42
Trust	−0.87	0.14	<0.001	0.29	-0.73	0.13	<0.001	0.33
Literacy	−0.77	0.14	<0.001	0.32	-0.69	0.13	<0.001	0.33
Scientific Content x Trust	−0.30	0.14	0.032	0.43	-0.30	0.11	0.008	0.43
Scientific Content x Literacy	−0.10	0.14	0.492	0.48				
Trust x Literacy	0.32	0.13	0.016	0.58				
Scientific Content x Trust x Literacy	0.11	0.13	0.407	0.53				

The full model includes all terms and their interactions. The final model is the best fitting-model of all combinations of predictors using cross-validation. Terms are abbreviated across rows: "Trust" represents trust in science, "Literacy" represents methodological literacy, and "x" denotes an interaction between variables. Terms are also abbreviated across columns: *B* stands for logit estimate (log of odds), *SE* stands for standard error of the beta, *Prob* stands for probability. For each term except the intercept, probability is the increased probability of dissemination associated with the term. For the intercept, it is the average probability of dissemination holding constant all predictors in the model

Table 3
Estimated marginal means of belief and estimated probability of dissemination across Experiments 1–3.

		High trust		Low Trust	
		Scientific content	No scientific content	Scientific content	No scientific content
Experiment					
Belief *M* (95% CI)	1	3.77 (3.62–3.92)	2.90 (2.77–3.04)	3.82 (3.68–3.95)	3.90 (3.76–4.04)
	2	3.48 (3.30–3.66)	2.83 (2.65–3.02)	3.55 (3.38–3.73)	3.32 (3.14–3.51)
	3	3.59 (3.40–3.78)	2.98 (2.80–3.16)	3.96 (3.78–4.13)	3.77 (3.62–3.92)
Dissemination Probability (95% CI) (95% CI)	1	0.76 (0.67–0.83)	0.59 (0.49–0.69)	0.90 (0.84–0.94)	0.92 (0.86–0.95)
	2	0.58 (0.48–0.67)	0.46 (0.36–0.56)	0.59 (0.50–0.68)	0.53 (0.43–0.62)
	3	0.78 (0.70–0.84)	0.49 (0.39–0.60)	0.89 (0.82–0.93)	0.90 (0.83–0.93)

The table represents the estimated marginal means of belief and increased probability of dissemination for Experiments 1–3 with the 95% lower and upper bound CI (Confidence Intervals) below each. Within each experiment, estimations are split into four columns representing participants with high trust in science (one standard deviation above the mean) in the scientific content condition (left side) and the non-scientific content condition, and participants with low trust in science in the second set of columns, including those in the scientific content condition and those in the non-scientific content conditions. All estimates are generated using the *R* package emmeans (Russell, 2020). All estimates are based on the final models presented in Table 2, except for estimates predicting dissemination in Experiment 2, in which the final model did not include the interaction. For Experiment 2, the estimates predicting dissemination are based on the full model.

probabilities across scientific and non-scientific conditions for participants with low and high levels of trust in science.

To assess sensitivity of effects on dissemination, we used G*Power (Erdfelder et al., 2009), selecting the sensitivity analysis option with two-tailed logistic regression (z test family), inputting 0.80 for power, with 532 participants, with alpha at 0.05, and two groups. We entered Pr $(Y = 1|X = 1)$ HO = 0.57 because that was the increased probability for the main effect of scientific content and Pr$(Y = 1|X = 1)$ HO = 0.63 for the interaction. The sensitivity analysis showed that the required *odds ratio* would be 1.28 for the main effect and 1.29 for the interaction, compared to the actual *odd's ratio of* 1.34 for the main effect and 1.63 for the interaction.

7. Preregistered experiment 2: replication with a nationally representative sample

We conducted a replication of Experiment 1 using a sample obtained from the company Dynata (Home - Dynata, 2021), with sampling designed to be nationally representative of the U.S. on gender, race/ethnicity, education, age, household income, and census region, with a 5% margin (Dynata, personal communication, February 26, 2021). The sample included 645 participants (excluding 52 participants who began but did not complete the study). We excluded the data of 173 participants for not passing a simple attention check in which they were asked to write "yes" in a blank box, leaving us with a total *N* of 472, including 205 males, 264 females, and three who identified as another gender, ages 18–99 years old, $M = 50.64$, $SD = 16.15$. On a scale to assess political ideology, from "Strong liberal" (1) to "Strong Conservative" (5), the average level of political ideology was 3.08 (again closest to "True moderate"), $SD = 1.30$. On a scale to assess formal education, from "Elementary School" (1) to "Doctoral degree" (6), the average level of education reported was 4.50 (between "Bachelor's degree" and "Master's degree"), $SD = 1.96$. Within the sample for analyses, 81.82% identified as white (including 77.95% of the sample which identified as white and not Hispanic), 10% identified as Black or African American, 1.36% identified as Native American (including Alaska Native), 4.09% identified as Asian, and 10% identified as Hispanic or Latino. As in Experiment 1, the experiment involved a 2 (content: scientific vs. not scientific) x continuous (measure of trust in science) x continuous (measure of methodological literacy) design. Data for Experiment 2 was collected between July 6th and July 15th, 2020.

As in Experiment 1, participants were randomly assigned to receiving either the scientific content ($N = 240$) or the non-scientific content ($N = 232$) condition. Experiment 2 deviated from Experiment 1 only in that we used a shorter version of the methodological literacy measure ($M = 1.94$, $SD = 1.07$), for brevities and cost's sake, with just four items, and that the dissemination item referred to a vote for sharing the research online rather than specifically within a class (see Supplement Part G for exact wording). We again used a Rasch model to determine scale reliability, which demonstrated a collapsed deviance of 46.06 with 12 degrees of freedom, $p < .001$, Pearson $R^2 = 0.31$, area under ROC: 0.82. The earlier measures of trust in science ($\alpha = 0.79$, $M = 3.35$, $SD = 0.70$), belief ($\alpha = 0.94$, $M = 3.30$, $SD = 1.06$), and dissemination (257 yes/215 no) were used, and the experimental content was identical. The preregistration of this experiment appears in Aspredicted.org (Link for Experiment 2 preregistration)[2] with author information blinded for review. We based our sample size on the power analysis discussed in the Methods of Experiment 1.

8. Results

8.1. Ruling out demand effects

The open-ended responses to the question about the purpose of the study were again coded to assess the possibility of demand effects. Five participants indicated that the research concerned whether knowledge about methodological literacy was associated with belief in the article. Analyses in Supplement Part E demonstrate that excluding these five participants did not alter the results from the final models presented in the main text. No participant guessed our critical interaction between trust in science and scientific content.

8.2. Main analyses

Tables 1-2 present both the full models and the best fitting models predicting belief and dissemination, respectively. Table 3 displays estimated levels of belief and probability of dissemination across scientific and non-scientific content conditions and levels of trust in science. The best fitting model for belief included scientific content, trust in science, methodological literacy, and the interaction between scientific content and trust in science (see Fig. 3 of Supplement Part D). The best fitting model for dissemination included only the main effects of methodological literacy and scientific content, suggesting that neither trust in science, nor any of the interactions added predictive value for dissemination (see Fig. 4 of Supplement Part C).

8.3. Belief

As hypothesized and found in Experiment 1, the effect of scientific content was moderated by trust in science, as indicated by a significant interaction between these two variables (see Table 1). At higher (one standard deviation above the mean) levels of trust in science, scientific content led to stronger belief than the absence of scientific content, $F(1, 459) = 24.85$, $p < .001$, $\eta p^2 = 0.04$. At lower (one standard deviation below the mean) levels of trust in science, the effect of scientific content on belief was just marginally significant, $F(1, 459) = 3.22$, $p = .074$, $\eta p^2 = 0.04$. Also as hypothesized, the presence of scientific content ($M = 3.52$, $SD = 0.98$) led to stronger belief than its absence ($M = 3.08$, $SD = 1.08$; see main effect in Table 1), and trust in science and methodological literacy were each associated with weaker belief in the misinformation.

To assess sensitivity of effects on belief, we used G*Power (Erdfelder et al., 2009), selecting the sensitivity analysis option with ANCOVA (F test family), inputting 0.80 for power, with 472 participants, one within degree of freedom, with alpha at 0.05, two groups, and three covariates. The sensitivity analysis showed that the required *Cohen's f* would be 0.13, compared to the actual *Cohen's f* of 0.22 for the main effect of scientific content and 0.11 for the interaction.

8.4. Dissemination

The cross-validation suggested that the final model predicting dissemination should only include scientific content and methodological literacy. In contrast to our hypotheses, although the pattern of results was directionally consistent, scientific content and trust in science did not interact in a significant fashion. Scientific content did exert a significant main effect, increasing the probability of dissemination. Trust in science did not significantly predict dissemination, but methodological literacy was associated with a lower probability of dissemination.

To assess sensitivity of effects on dissemination, we used G*Power (Erdfelder et al., 2009), selecting the sensitivity analysis option with two-tailed logistic regression (z test family), inputting 0.80 for power, with 472 participants, with alpha at 0.05, and two groups. We entered $\Pr(Y = 1|X = 1)$ HO $= 0.60$ because that was the increased probability for the main effect of scientific content, and we specified $\Pr(Y = 1|X = 1)$ HO $= 0.53$ for the interaction. The sensitivity analysis showed that the required *odds ratio* would be 1.31 for the main effect and 1.30 for the interaction, compared to the actual *odd's ratio of* 1.51 for the main effect and 1.12 for the interaction.

9. Preregistered experiment 3: trust in science, methodological literacy and the impact of GMO pseudo-science

9.1. Methods

9.1.1. Participants and design

We next conducted a replication of Experiments 1–2 by varying the context of the pseudoscience and thus showing generalizability across issues. The misinformation used in this study concerned the unsubstantiated but widely believed tumor-inducing effects of GMOs and an ostensible conspiracy by the agrochemical company, Monsanto. We recruited 605 participants including 388 males and 217 females, ages 18–74, $M = 36.36$, $SD = 11.29$ again using Amazon's MTurk (Buhrmester et al., 2018) limiting eligibility to participants within the United States. On a scale to assess political ideology, from "Strong liberal" (1) to "Strong Conservative" (5), the average level of political ideology was 2.83, slightly more liberal than the prior two samples, but again closest to "True moderate", $SD = 1.35$. On a scale to assess formal education, from "Elementary School" (1) to "Doctoral degree" (6), the average level of education reported was 3.85 (closest to "Bachelor's degree"), $SD = 0.88$.[3] Experiment 3 was pre-registered on the Open Science Framework (Link for Experiment 3 preregistration here)[4] with author information hidden for review. Of those who responded to questions about race and ethnicity, 68.59% identified as white, 11.57% identified as African American, 7.93% identified as Hispanic, 8.26% identified as Asian, 2.81% identified as Native American, 0.17%

[2] The full URL for Experiment 2 preregistration can be copied and pasted into a browser: https://aspredicted.org/blind.php?x=sy8uf5

[3] Although we had pre-registered an attention check, we were unable to use the attention check in Experiment 3 simply because there was a survey error that made it uninterpretable.

[4] The full URL for Experiment 3 preregistration can be copied and pasted into a browser: https://osf.io/yujcx/?view_only=d4474bc6f18f4147a5c07d6980e87ac4

identified as Pacific Islander, and 0.66% identified as "Other". As for the prior experiments, the experiment involved a 2 (content: scientific vs. not scientific) x continuous (measure of trust in science) x continuous (measure of methodological literacy) design. We based our sample size on the power analysis discussed in the Methods section of Experiment 1. Data for Experiment 3 was collected between May 6th and May 7th, 2020.

9.2. Procedures, materials and measures

Experiment 3 was identical to Experiments 1–2 except for the content of the messages. We also included two separate messages for each condition following recommendations for experimental stimuli to include more than one instantiation of the condition (Judd, Westfall, & Kenny, 2012) for both external and construct validity (Wells & Windschitl, 1999). Both sets of stimuli were taken from actual websites (Are GMO Dangers THAT Big Of A Deal? | The Family That Heals Together, 2021; White, 2016) propagating the idea that GMOs cause tumors and that there was a conspiracy to conceal this information from the public. The stimuli are pictured in Supplement Part G. Both sets of stimuli mentioned a study of mice developing tumors following GMO consumption (Séralini et al., 2012, now retracted). One included a benign picture of a syringe injecting into hanging fruit, and discussed macronutrients claimed to be different in modified (vs. non-modified) foods, introduced a subtle accusation of bias in GMO studies being funded by GMO companies, and referred to studies finding tumors in mice fed GMOs broadly. The other set of stimuli focused more on the mice with vivid pictures and made explicit accusations of a cover-up, with details of an experiment published (but now retracted) in a peer-reviewed journal supporting the accusations of GMOs causing tumors. The text involved real fragments of journalistic style coverage of this paper, which was actually published and later retracted (Séralini et al., 2012; now retracted) going into detail about the studies, taken from an actual anti-GMO website (GMO News | GMO News and Information, 2021). The non-scientific content condition involved the same arguments about GMOs but did not include scientific credentials and were written in the style of activist reports. As in similar materials in the real world, the information included pictures and a source attribution to a website (Adams, 2012) referencing the now-retracted paper on the topic (Séralini et al., 2012; now retracted). As explained presently, stimulus set was considered in our analysis and showed to not moderate the trust in science and scientific content interaction (Supplement Part D). The final samples sizes were 284 and 321 for the scientific and non-scientific content conditions.

As in Experiment 1, following distractor items, we assessed the behavior of *dissemination* (159/26% voting "no" and 446/74% voting "yes"), participants' *belief* ($\alpha = 0.91$, $M = 3.51$, $SD = 1.01$), *trust in science* ($\alpha = 0.84$, $M = 3.35$, $SD = 0.80$), and *methodological literacy* ($M = 3.85$, $SD = 2.04$), using measures identical to those in Experiments 1–2, except that we used the full eight items for methodological literacy again, as in Experiment 1, due to the lower costs of using M-Turk participants. As in Experiments 1–2, we used item response theory to assess the reliability of the methodological literacy measure and obtained the goodness of fit statistics of a Rasch model of the items. The collapsed deviance with 56 degrees of freedom was 274.49, $p < .001$, Pearson $R^2 = 0.26$, area under $ROC = 0.79$.

10. Results

10.1. Ruling out demand effects

As before, we coded participants' responses to the debriefing question. Four participants guessed the purpose of testing whether methodological literacy was associated with less belief. Analyses in Supplement Part E demonstrate that excluding these participants did not change the results from the final models presented in the main text. No participant guessed our critical interaction between trust in science and scientific content.

10.2. Main analyses

We conducted the same set of analyses used in the prior experiments to test our central hypothesis that scientific trust would increase susceptibility to pseudoscientific content. These included ANCOVA to test our hypothesis about belief and logistic regression to test our hypothesis with the behavioral outcome of dissemination. As in Experiments 1–2, we use cross-validation to decide upon our final model. The analyses in Fig. 5 of the supplementary files (Supplement Part C) suggested that the best-fitting model to explain belief was the full model including all main effects and interactions between scientific content, trust in science, and methodological literacy, followed closely by the model with just main effects and the two-way interaction between scientific content and trust in science. Furthermore, the best-fitting model to predict dissemination was the model including main effects and the interaction between scientific content and trust in science. The results from the analyses predicting belief and dissemination appear in Tables 1-2, and the estimated marginal means of belief and probabilities of dissemination across the scientific and non-scientific content conditions among participants with low and high levels of trust in science appear in Table 3.

10.3. Belief

As before, results supported the hypothesis that the effect of scientific content was moderated by trust in science, as indicated by a significant interaction between these two factors, (see Table 1). Among participants with higher levels of trust in science (one standard deviation above the mean), scientific content strongly influenced belief, $F(1, 597) = 20.87$, $p < .001$, $\eta p^2 = 0.05$. Among participants with lower levels of trust in science (one standard deviation below the mean), there was no significant effect of scientific content, $F(1, 597) = 2.64$, $p = .105$, $\eta p^2 = 0.05$.

Also as predicted, there was a significant main effect of the scientific content condition ($M = 3.72$, $SD = 0.90$) leading to stronger belief relative to the non-scientific content condition ($M = 3.33$, $SD = 1.06$). Trust in science and methodological literacy were both associated with lower levels of belief as main effects (see Table 1).

Although not predicted, there was also a significant two-way interaction between scientific content and methodological literacy. At high (one standard deviation above the mean) levels of methodological literacy, the effect of scientific content increasing belief was strong, $F(1, 597) = 23.02$, $p < .001$, $\eta p^2 = 0.05$, whereas it was not significant for those with low levels of methodological literacy, $F(1,597) = 2.82$, $p = .093$, $\eta p^2 = 0.05$. However, this interaction between scientific content and methodological literacy was not present in the other studies and did not replicate for dissemination.[5] Also not predicted, trust and methodological literacy interacted with one another. For those with high levels of methodological literacy, trust was related to lower levels of belief, $B = -0.54$, $SE = 0.07$, $p < .001$, but this protective relation was less strong among those with low methodological literacy, $B = -0.25$, $SE = 0.06$, $p = .010$.

To assess sensitivity of effects on belief, we used G*Power (Erdfelder

[5] An analysis detailed in Supplement Part D suggested that the interaction between methodological literacy and scientific content occurred only in the second set of stimuli with pictures of mice, detailing experimental, peer-reviewed research that has, in reality been retracted (Séralini et al., 2012; now retracted). Its occurrence strictly within this stimulus set makes sense in light of the reference to specific, peer-reviewed, published experimental data as, not privy to the details of retraction, these are criteria that methodological literacy trains people to identify. The finding made experimentally testing critical evaluation as a casual factor desirable. We conducted such test in Experiment 4.

et al., 2009), selecting the sensitivity analysis option with ANCOVA (F test family), inputting 0.80 for power, with 605 participants, one within degree of freedom, with alpha at 0.05, two groups, and six covariates. The sensitivity analysis showed that the required *Cohen's f* would be 0.11, compared to the actual *Cohen's f* of 0.22 for the main effect of scientific content and 0.20 for the interaction.

10.4. Dissemination

As hypothesized, the effect of scientific content was moderated by trust in science, as indicated by a significant interaction between the two terms, b(logit) = 0.60, $SE = 0.23$, $z = 2.67$, $p = .008$. Among participants with higher levels of trust in science, scientific content led to higher probability of dissemination by 0.78, b (logit) = 1.26, $SE = 0.27$, $z = 4.74$, $p < .001$. In contrast, among participants with lower trust in science, there was no effect of scientific content, b (logit) = 0.05, $SE = 0.38$, $z = 0.13$, $p = .894$.

Also as predicted, as a main effect there was a 0.66 higher probability of dissemination when the misinformation had scientific contents, b (logit) = 0.65, $SE = 0.23$, $z = 2.79$, $p = .005$, whereas trust in science and methodological literacy were each associated with a lower probability of dissemination by 0.26, B(logit) = −1.03, $SE = 0.17$, $z = -6.09$, $p < .001$, and by 0.33, B (logit) = −0.69, $SE = 0.13$, $z = -5.23$, $p < .001$, respectively.

To assess sensitivity of effects on dissemination, we used G*Power (Erdfelder et al., 2009), selecting the sensitivity analysis option with two-tailed logistic regression (z test family), inputting 0.80 for power, with 605 participants, with alpha at 0.05, and two groups. We entered Pr $(Y = 1|X = 1)$ HO = 0.66 because that was the increased probability for the main effect of scientific content, and we specified Pr$(Y = 1|X = 1)$ HO = 0.65 for the interaction. The sensitivity analysis showed that the required *odds ratio* would be 1.28 for the main effect and 1.27 for the interaction, compared to the actual *odd's ratio of* 1.92 for the main effect and 1.83 for the interaction.

11. Experiment 4: experimental induction of critical evaluation

11.1. Methods

11.1.1. Participants and design

Experiment 4 included 613 participants as part of a sample provided by Dynata (*Home - Dynata*, n.d.), including 249 males, 276 females, and three participants who identified with another gender, ages 18–88, $M = 45.68$, $SD = 16.78$. Of the 613 participants, 382 passed a simple attention check in which they are instructed to write "yes" in a blank box. To address potential issues arising from the large number of participants not passing attention checks, we present analyses based both on the full sample and on this restricted sample below. On a scale to assess political ideology, from "Strong liberal" (1) to "Strong Conservative" (5), the average level of political ideology was 3.00 in the restricted sample, $SD = 1.25$, and 2.96 (closest to "True moderate"), $SD = 1.29$ in the full sample. On a scale to assess formal education, from "Elementary School" (1) to "Doctoral degree" (9), the average level of education reported was 4.41, $SD = 1.88$ in the restricted sample, and 4.50, $SD = 2.05$ in the full sample (between "Associate degree" and "Bachelor's degree"). Within the restricted sample, 85.55% of participants identified as white (82.15% as white and not Hispanic) in the restricted sample, compared to 77.55% of participants (74.22% identifying as white and not Hispanic) in the full sample; 10.20% of participants identified as Black or African American in the restricted sample, compared to 17.05% in the full sample; 9.02% of participants identified as Hispanic or Latino in restricted sample, compared to 13.42% of those in the full sample; 2.55% of participants who identified as Asian in the restricted sample, compared to 2.91% in the full sample; 0.85% of participants identified as Native American in the restricted sample, compared to 1.04% in the full sample; 0.57% of participants marked "Other" in the restricted sample, compared to 0.62% of participants in the full sample; reported multiple races in restricted sample, compared to 0.21% in the full sample; in the restricted sample, 0% of participants identified as Native Hawaiian/Pacific Islander, compared to 0.42% in the full sample. The experiment involved a 2 (content: scientific vs. not scientific) x 3 (mindset: critical evaluation, trust in science, or control). For Experiment 4, we conducted a power analysis using GPower (Erdfelder et al., 2009), specifying a Cohen's f of 0.18, for an ANCOVA with six groups. Data for Experiment 4 was collected between July 9th and July 15th, 2020.

11.2. Procedure, materials, and measures

We randomly assigned participants to two factors. The mindset manipulation randomly assigned participants to list experiences to induce either (a) a critical evaluation mindset ($N = 117$ within the restricted sample; $N = 174$ in the full sample), (b) a trust science mindset ($N = 139$ within the restricted sample; $N = 193$ in the full sample), or (c) a control mindset ($N = 126$ within the restricted sample; $N = 187$ in the full sample). The critical evaluation instructions read: "Please name 3 examples of people needing to think for themselves and not blindly trust what media or other sources tell them. This could be regarding science or any type of information, either from history, current events, or your personal life" (critical evaluation mindset condition). The trust in science mindset instructions read: "Please name 3 examples of science saving lives or otherwise benefiting humanity. This could be in the medical sciences or chemistry, physics, or any type of science." The control mindset instructions read: "Please name 3 examples of landscapes that were unusual or interesting to you. This could be near your home, something you observed while travelling, or even that you saw through television or internet." Following the mindset instructions, participants were randomly assigned to either the scientific content ($N = 190$ within the restricted sample; $N = 274$ within the full sample) or non-scientific content condition ($N = 192$ within the restricted sample; 272 in the full sample) with the GMO materials from Experiment 3, featuring the second stimulus set. Following this reading, participants responded to the same belief measure ($\alpha = 0.95$, $M = 3.39$, $SD = 1.12$ within the restricted sample; $\alpha = 0.93$, $M = 3.36$, $SD = 1.07$ the in full sample). As preregistered, we did not measure dissemination in Experiment 4. The preregistration of this experiment appears on AsPredicted.org (Experiment 4 preregistration)[6] with author information hidden for review. Analyses were conducted using ANOVA with sum to zero contrasts (effects coding) for the three-level mindset condition variable.

12. Results

12.1. Ruling out demand effects

Coding of open-ended responses to the question regarding the purpose of the study did not indicate demand effects. No participants inferred the purposes that were coded for in Experiments 1–3. Twenty-four participants did indicate that the study involved critical thinking or trust of science. However, analyses in Supplement Part E demonstrate that excluding these participants did not change results substantively.

12.2. Main analyses

As hypothesized, reading the scientific content ($M = 3.67$, $SD = 0.97$ in the restricted sample; $M = 3.58$, $SD = 0.99$) led to stronger belief than reading the non-scientific content, ($M = 3.12$, $SD = 1.19$ within restricted sample; $M = 3.14$, $SD = 1.10$ in the full sample), both within the restricted sample $F(1, 375) = 25.96$, $p < .001$, $np^2 = 0.06$, and the

[6] The full URL for Experiment 4 preregistration can be copied and pasted onto a browser, https://aspredicted.org/blind.php?x=5kc76m

full sample, $F(1, 375) = 25.00$, $p < .001$, partial eta squared = 0.04. There was also a main effect of critical evaluation in both the restricted sample, $F(2, 375) = 3.33$, $p = .037$, $\eta p^2 = 0.02$, and the full sample, $F(2, 531) = 3.75$, $p = .024$, $\eta p^2 = 0.02$. In contrast to hypotheses, there was no significant interaction between the two factors in either the restricted sample, $F(2, 375) = 1.56$, $p = .212$, $\eta p^2 = 0.01$, or the full sample, $F(2, 531) = 1.53$, $p = .218$, $\eta p^2 = 0.01$, suggesting that the main effect of the critical mindset held regardless of whether the misinformation contained scientific references. Specifically, the critical evaluation condition ($M = 3.23$, $SD = 1.10$ in the restricted sample; $M = 3.19$, $SD = 1.04$ in the full sample) led to weaker belief than the control condition ($M = 3.54$, $SD = 1.13$ in the restricted sample; $M = 3.43$, $SD = 1.08$ in the full sample), for contrast, $t(375) = 2.58$, $p = .010$, in the restricted sample and $t(531) = 2.52$, $p = .012$ in the full sample. Within the restricted sample, the critical mindset condition ($M = 3.23$, $SD = 1.10$) was not significantly different from the trust science mindset ($M = 3.40$, $SD = 1.11$), for contrast, $t(375) = -1.23$, $p = .220$. However, within the full sample, consistent with hypotheses, the critical mindset condition ($M = 3.19$, $SD = 1.04$) produced weaker belief than did the trust condition ($M = 3.44$, $SD = 1.07$), $t(531) = -2.23$, $p = .026$. In contrast to hypotheses, there was no significant difference between the trust in science and control conditions, neither in the restricted sample, $t(375) = 1.44$, $p = .151$, nor in the full sample, $t(531) = 0.34$, $p = .737$.

To assess sensitivity of effects on belief, we used G*Power (Erdfelder et al., 2009), selecting the sensitivity analysis option with ANCOVA (F test family), inputting 0.80 for power, with alpha at 0.05, with 613 participants and (for a separate analysis) 382 for the reduced sample. For the effect of scientific content on belief, we specified one within degree of freedom, two groups, and two covariates. The analysis showed that a *Cohen's f* of 0.13 would be required for the main effect of scientific content, compared to the actual *Cohen's f* of 0.21. For the effect of mindset and the interaction between mindset and scientific content, we specified six groups and two within degrees of freedom. This analysis showed that the required *Cohen's f* would be 0.13, compared to the actual *Cohen's f* of 0.12 for the main effect of mindset and 0.08 for the interaction.

12.3. Meta-analysis

We conducted a meta-analysis to summarize the magnitude and significance of the main effect of scientific content (Experiments 1–4), the interaction between scientific content and trust in science (Experiments 1–3), and the relation of critical evaluation (methodological literacy in Experiments 1–3 and the effect of the mindset factor in Experiment 4) using the *R* packages metafor (Viechtbauer, 2010) and esc (Lüdecke, 2019) with Hedge's *g* as the effect size to correct for the potential bias of small sample sizes (Lakens, 2013). "LLCI" and "ULCI" are used to indicate lower and upper-level 95% confidence intervals, respectively. We used sample sizes from the full models which included all possible interaction terms to estimate them conservatively. The *R* code for all effect size computations and the meta-analyses are included in Supplement Part F.

12.4. Belief

Across Experiments 1–3, which manipulated scientific content and measured trust in science, there was a small (Cohen, 1992) interaction between the two factors, $g = 0.27$, $se = 0.11$, $z = 2.43$, $p < .015$, [LLCI: 0.0519, ULCI: 0.4881]. Among participants with higher levels of trust in science, there was a medium effect of scientific content increasing susceptibility, $g = 0.50$, $SE = 0.13$, $z = 4.00$, $p < .001$, [LLCI: 0.2560, ULCI: 7487]. In contrast, among participants with lower levels of trust in science, there was no effect of scientific content, $g = 0.06$, $se = 0.05$, $z = 1.32$, $p = .185$, [LLCI: −0.0298, ULCI: 0.1540]. Across the four experiments, there was a small-medium-sized main effect of scientific content leading to stronger belief, $g = 0.43$, $se = 0.05$, $z = 9.56$, $p < .001$, [LLCI: 0.3450, ULCI: 5229]. Results also supported the hypothesis that critical evaluation reduces belief, $g = 0.37$, $SE = 0.04$, $z = 8.71$, $p < .001$, [LLCI: 0.2904, ULCI: 0.4590]. Fig. 1 displays the forest plots for all the predicted effects for belief based on the main effects and interactions between scientific content and trust, and Fig. 4 displays the forest plots for all the predicted effects for belief based on critical evaluation (methodological literacy).

12.5. Dissemination

The effects were similar for dissemination, with a significant, though small interaction between trust in science predicting likelihood of dissemination, $g = 0.25$, $se = 0.12$, $z = 2.08$, $p = .038$, [LLCI: 0.0138, ULCI: 4470]. For those with high levels of trust in science, there was a (roughly) medium-sized effect of scientific content increasing dissemination, $g = 0.48$, $se = 0.13$, $z = 3.58$, $p < .001$, [LLCI: 0.2176, ULCI: 7433]. For those with low levels of trust in science, there was no effect of scientific content increasing dissemination, $g = 0.02$, $se = 0.12$, $z = 0.16$, $p = .872$, [LLCI: −0.2107, ULCI: 2485]. The results also supported the hypothesis that methodological literacy and critical evaluation predicted lower dissemination, $g = -0.41$, $se = 0.12$, $z = -3.46$, $p = .001$, [LLCI: −0.6421, ULCI: −0.1774]. Fig. 1 displays the forest plots for all the predicted effects for dissemination based on the main effects and interactions between scientific content and trust in science. Fig. 2 displays the forest plots for all the predicted effects for dissemination based on scientific content and trust in science.

13. General discussion

Our four experiments and meta-analysis demonstrated that people, and in particular people with higher trust in science (Experiments 1–3), are vulnerable to misinformation that contains pseudoscientific content. Among participants who reported high trust in science, the mere presence of scientific labels in the article facilitated belief in the misinformation and increased the probability of dissemination. Thus, this research highlights that trust in science ironically increases vulnerability to pseudoscience, a finding that conflicts with campaigns that promote broad trust in science as an antidote to misinformation (see also Oreskes, 2019) but does not conflict with efforts to instill trust in conclusions about the specific science about COVID-19 (Fauci, Lane, & Redfield, 2020) or climate change (Ruths, 2019).

In terms of the process, the findings of Experiments 1–3 may reflect a form of heuristic processing (Todorov, Chaiken, & Henderson, 2002). Complex topics such as the origins of a virus or potential harms of GMOs to human health include information that is difficult for a lay audience to comprehend, and requires acquiring background knowledge when reading news. For most participants, seeing scientists as the source of the information may act as an expertise cue (Chaiken, 1980) in some conditions, although source cues are well known to also be processed systematically (Erb & Kruglanski, 2005; Petty & Cacioppo, 1986). However, when participants have higher levels of methodological literacy, they may be more able to bring relevant knowledge to bear and scrutinize the misinformation. The consistent negative association between methodological literacy and both belief and dissemination across Experiments 1–3 suggests that one antidote to the influence of pseudoscience is methodological literacy. The meta-analysis supports this. However, the protective benefits of methodological literacy may be limited to instances in which aspects of the methodology are presented

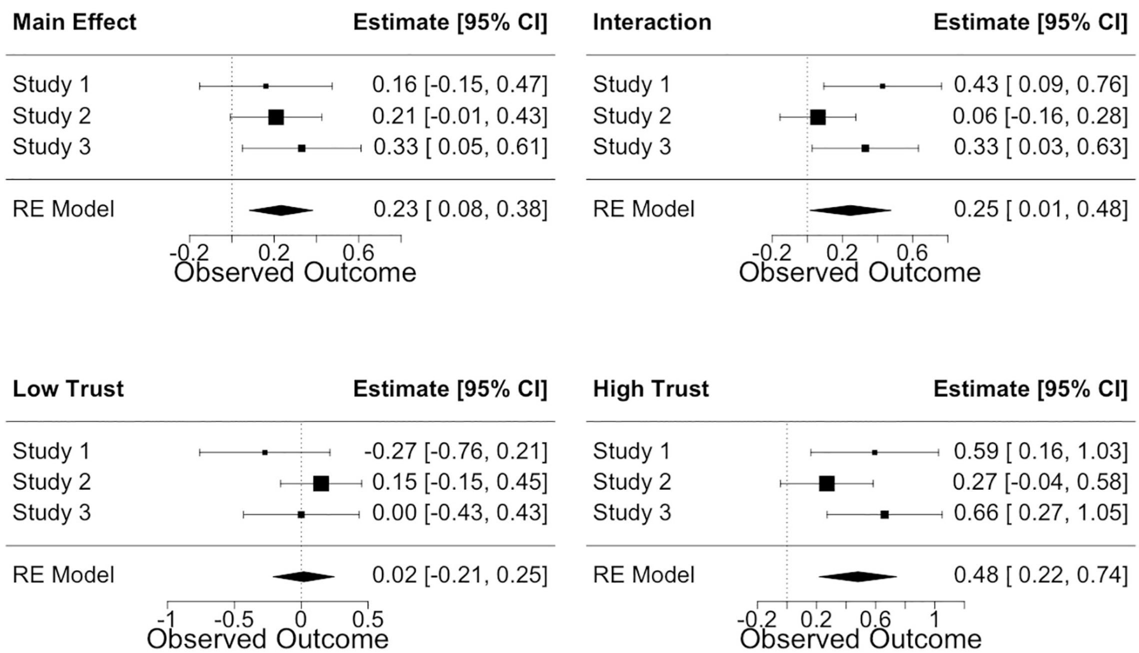

Fig. 2. Forest plots of scientific content and its interaction with trust in science predicting dissemination. Using Hedge's *g* to estimate effect size, the plots above show effect sizes for each study with 95% confidence intervals on the right-hand side and the estimated average effect in a random effects model at the bottom. This includes plots show the main effect of scientific content on dissemination across Experiments 1–4 (top left), the estimated two-way interaction between scientific content and trust in science across Experiments 1–3 (top right), the estimated main effect of scientific content for those with low trust in science across Experiments 1–3 (bottom left), and the estimated main effect of scientific content for those with high trust in science across Experiments 1–3 (bottom right).

without omitting broader, important context such as retraction.[7] A more sustainable solution may involve instilling both knowledge and skills such as methodological literacy, as well as a motivation to systematically process information.

Study 3 also showed an interaction between methodological literacy and scientific content, whereby scientific content increased beliefs more among those with higher levels of methodological literacy. The finding, though not predicted, is in line with other work showing that various measures of both scientific knowledge and skillsets such as numeracy and scientific knowledge can be associated with greater polarization rather than endorsement of scientific information (Kahan et al., 2012; Scheufele, 2014). However, recent research has offered a critique to research on motivated reasoning accounts (Tappin et al., 2020), and the interaction between scientific content and methodological literacy did not replicate in the other studies.

Although not measured in the current research, the emerging literature on scientific curiosity may also offer solutions against endorsement of pseudoscientific misinformation (Kahan et al., 2017). This literature shows that people who are curious about scientific topics, rather than certain about their answers, are more likely to remain open minded about the information, neither endorsing not rejecting claims without proper scrutiny. Therefore, future research should examine the impact of science curiosity in the context of pseudoscience.

14. Limitations

A key limitation to our study, of course, is that the processes we identify are likely to occur when the misinformation is not accompanied with scientific corrections or critiques. However, not all scientists agree on all issues (Pew Research Center, 2015), scientists submit evidence that is later retracted (Top 10 Most Highly Cited Retracted Papers – Retraction Watch, 2021) and those who promote pseudoscientific misinformation can always find a source with seemingly credible credentials. Misinformation can always be presented with support from isolated scientists regardless of their standing or consensus among the majority, as exemplified in the 45th U.S. President pointing to medical doctors supporting his plan on COVID-19 (Alemany, 2020).

Importantly, the conclusion of our research is not that trust of science is risky but rather that, applied broadly, trust in science can leave people vulnerable to believing in pseudoscience. However, the consistent negative association between trust (as a main effect) and belief indicates that trust in science is generally protective, just not for misinformation with pseudoscientific contents. Although scientific content increased acceptance of misinformation among those who trust science, we did not include conditions involving accurate information, and other research has found that trust in science increases acceptance of accurate scientific contents (Motta 2018; Stecula et al., 2020; Merkley 2020; Merkley et al., 2020). Future research should investigate these boundary conditions more carefully.

Other measures of trust in science may also lead to different results particularly with new measures that do not reflect deference to science. Deference to scientific authority involves indiscriminately believing information from sources carrying scientific credentials and predicts support for agricultural biotechnology (Brossard & Nisbet, 2006). Whether deference differs from trust in science should be investigated in the future.

15. Conclusion

As COVID-19 and climate change highlight the need for decisions based on scientific evidence, we must still defend from pseudoscientific claims that undermine the legitimate voice of scientific consensus (Oreskes, 2019). Although cynicism of science could have disastrous impacts (Rutjens et al., 2018), our results suggest that advocacy for

[7] Noteworthy, Experiment 3 showed a very small but significant, unexpected interaction between scientific content and methodological literacy suggesting that those with higher levels of literacy may be more susceptible to belief when it includes scientific content. See Experiment 3 Results, Supplement Part F, and the above footnote. However, this interaction was not present in any of the other experiments.

trusting science must go beyond scientific labels, to focus on specific issues, critical evaluation, and the presence of consensus among several scientists as a source or claims of scientific studies in support of a claim (Oreskes, 2019). Fostering trust in the "healthy skepticism" inherent to the scientific process may also be a critical element of protecting against misinformation, as Experiment 3 and past research suggested that even people who are knowledgeable can be vulnerable to misinformation with scientific content (Kahan et al., 2012). Empowering people with knowledge about the scientific validation process (Gormally et al., 2012) and the motivation to be critical and curious (Motta et al., 2019) may give audiences the resources they need to dismiss fringe but dangerous pseudoscience.

Footnotes

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jesp.2021.104184.

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