A Preregistered Replication of “Inoculating the Public against Misinformation about Climate Change”

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Declarations of interest

None.

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Abstract

A strong consensus exists amongst climate scientists that the Earth is warming, and that this warming is due to anthropogenic greenhouse gas emissions. Members of the public are nevertheless frequently exposed to misinformation about climate change (and the degree of scientific consensus on climate change). One strategy to combat such misinformation is attitudinal “inoculation”—exposing individuals to a weakened item of misinformation along with a pre-emptive refutation. Van der Linden, Leiserowitz, Rosenthal, & Maibach (2017) reported that exposing participants to misinformation reduced the extent to which the participants perceived there to be a scientific consensus about climate change, but that the effect of this misinformation was successfully countered by an attitudinal inoculation. In this study, we report a preregistered replication of van der Linden et al. (2017). Our replication study used a mixed between-within design, with data collected via Mechanical Turk ($N = 792$). We were able to replicate some (but not all) of van der Linden et al.’s findings. Specifically, we found that providing information about the scientific consensus on climate change increased perceptions of scientific consensus, as did an inoculation provided prior to provision of misinformation. However, we were unable to replicate their finding that an inoculation counteracted the effect of misinformation to a greater extent than simply providing information about scientific consensus—although this may have been due to a ceiling effect in our study. Our preregistration and data are available at <https://osf.io/8ymj6/>

Keywords: Climate change, environmental psychology, misinformation, replication, open science, inoculation.

Highlights

- We report a replication of a study by van der Linden et al. (2017)
- We tested the effect of inoculation on perceived scientific consensus about climate change
- We provided an inoculation to participants before exposing them to misinformation
- The inoculation successfully countered the effect of the misinformation
- The inoculation increased perceived scientific consensus

CRediT Author Statement

Matt N. Williams: Conceptualization; Methodology; Formal analysis; Data curation; Writing – Review & Editing; Visualization; Supervision.

Christina M. C. Bond: Conceptualization; Methodology; Investigation; Writing – Original Draft.

1 Introduction

The Earth is warming, and human activities are primarily to blame (IPCC, 2014). This conclusion is the subject of a remarkably strong scientific consensus: Approximately 97% of actively publishing climate scientists agree that the Earth is warming and human activities are responsible for most of this warming (Cook et al., 2016). Despite this consensus amongst climate scientists, the public are divided in their beliefs about the causes (and existence) of climate change (Capstick, Whitmarsh, Poortinga, Pidgeon, & Upham, 2015; for international studies see Pelham, 2009). Climate change denial amongst some members of the public represents a barrier to effective conservation action on climate change (Bohr, 2016; Gifford, 2011).

Members of the public also tend to underestimate the degree of scientific consensus about climate change (e.g., Hamilton, 2016). One plausible reason for this is the sharing of inaccurate information about climate change in online and mainstream media (Farrell, 2016; Oreskes & Conway, 2010). A notable example of misinformation about climate change is the “Oregon petition”—a petition arguing that there is no evidence that greenhouse gas emissions could cause disruption to the Earth’s climate (“Global warming petition project,” n.d.). The petition claims to have over 31,000 signatories—although the summary of signatories by qualification on the petition website indicates that just 39 of these signatories have a formal educational qualification in climatology.

One potentially useful strategy for combating misinformation is that of *attitudinal inoculation*, an idea studied in social psychology for over 50 years (Anderson & McGuire, 1965). In this context, inoculation means preparing a person for the possibility that they may be exposed to misinformation by presenting them with a weak example of the misinformation along with a refutation (“refutational pre-empting”). This is believed to increase resistance to the misinformation, much in the same way that a vaccine confers resistance to a virus by

exposing the body to a weakened version of that virus. A large body of research has applied and tested inoculation interventions in contexts including health, politics and education (An & Pfau, 2004; Banas & Rains, 2010; Compton, Jackson, & Dimmock, 2016). As discussed by Compton (2019), inoculations can be presented both to individuals who already have a “desired” attitude or belief (“prophylactic” inoculation, designed to protect against challenges to the attitude or belief), or to individuals who do not (“therapeutic” inoculation, designed to *change* an attitude or belief).

An inoculation intervention was implemented in the context of communication about climate change by van der Linden et al. (2017, Study 2). Van der Linden et al. used a mixed between-within experimental design with 2,167 participants collected via Mechanical Turk (MTurk). They investigated how participants’ perceptions of the degree of scientific consensus about climate change were affected by exposure to accurate information about the scientific consensus on climate, as well as how participants were affected by counter-messaging (misinformation) about scientific consensus. They also investigated whether the effect of misinformation was buffered by two different forms of inoculation (a general, brief, inoculation and a more detailed inoculation). Their results indicated both the general and detailed inoculation messages reduced the effect of misinformation on participants’ beliefs about the scientific consensus on climate change.

These findings are important, because there is some evidence that the perception of a scientific consensus can serve as a “gateway” belief that increases belief in the reality of climate change, and increases support for public action (van der Linden, Leiserowitz, Feinberg, & Maibach, 2015; van der Linden, Leiserowitz, & Maibach, 2019; Kerr & Wilson, 2018a, but c.f. Kerr & Wilson 2018b). Van der Linden et al.’s study is also important because (unlike Experiment 1 of Cook, Lewandowsky, & Ecker, 2017) it found that providing inoculation in combination with a message about the scientific consensus on climate change

and misinformation increased perceived scientific consensus more than the consensus message and misinformation alone. Whether or not inoculation provides an added benefit beyond simple messages about scientific consensus is an important issue for scientists and other stakeholders who wish to counter misinformation about climate change in the public sphere (see Cook & Lewandowsky, 2011).

Van der Linden's study was a valuable contribution to the environmental psychology literature, but replicating it is important for several reasons. Firstly, the original study was not preregistered (see Nosek, Ebersole, DeHaven, & Mellor, 2018; Wagenmakers, Wetzels, Borsboom, van der Maas, & Kievit, 2012). Second, the study has been relatively influential in the academic literature, accruing more than 200 citations in the three years since its publication. Third, to our knowledge no close replication of van der Linden et al. (2017) has yet been reported in the academic literature¹.

Consequently, we replicated van der Linden et al.'s study, albeit with some small modifications. In doing so, our study tested 12 hypotheses (see Table 1). Some of the hypotheses (H2-H5) were based on hypotheses explicitly stated in van der Linden et al. The remainder were based on empirical findings reported in van der Linden et al. (the hypotheses in the original study were described quite briefly and did not fully elaborate what between-condition differences were expected). Our study utilised five different conditions (displayed in Table 3). On the advice of van der Linden, and in order to maximise statistical power, we utilised only the more detailed inoculation (which had produced larger effects in the original study), and not the brief/general inoculation.

Table 1

Hypotheses

Number	Hypothesis
<i>Within-subjects hypotheses</i>	

¹ Two experiments by Cook, Lewandowsky and Ecker (2017) also tested the effect of an inoculation intervention in combating misinformation about scientific consensus about climate change. However, these experiments used a different design and data analysis. Their experimental materials also differed somewhat from those in van der Linden et al. (e.g., they also used the Oregon petition image in a misinformation/counter-message condition, but with a different passage of accompanying text).

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- 1 Within condition 1 [control] there will be no change in the mean of perceived scientific agreement [between] pre-test and post-test.
 - 2 Within condition 2 [consensus-treatment] the mean of perceived scientific agreement will be higher [at] post-test than at pre -test.
 - 3 Within condition 3 [counter-message] the mean of perceived scientific agreement will be lower [at] post-test than at pre-test.
 - 4 Within condition 4 [consensus-treatment followed by counter-message] there will be no change in the mean of perceived scientific agreement [between] pre-test and post-test.
 - 5 Within condition 5 [consensus-treatment + inoculation followed by countermessage] the mean of perceived scientific agreement will be higher [at] post-test than pre-test.

Political affiliation hypotheses

- 6 The consensus only treatment participants* [condition 2] will have a larger effect for those who identify as Republicans and Independents compared to Democrats.
- 7 The change from pre-test to post-test in condition 4 (consensus-treatment + counter-message) is more negative for Republicans than Democrats or Liberals.

Between-subjects hypotheses

- 8 When controlling for differences in pretest scores, participants in the consensus-treatment condition (condition 2) will show higher mean levels of perceived scientific consensus than those in the control condition (condition 1).
- 9 When controlling for differences in pretest scores, participants in the counter-message condition (condition 3) will show lower mean levels of perceived scientific consensus than those in the consensus-treatment condition (condition 2).

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- 10 When controlling for differences in pretest scores, participants in the inoculation condition (condition 5) will show higher mean levels of perceived scientific consensus than those in the consensus treatment + counter-message condition (condition 4).
- 11 When controlling for difference in pretest scores, participants in the consensus-treatment condition (condition 2) will show higher mean levels of perceived scientific consensus than those in the consensus treatment + counter-message condition (condition 4).
- 12 When controlling for differences in pretest scores, participants in the counter-message condition (condition 3) will show lower mean levels of perceived scientific consensus than participants in the inoculation condition (condition 5).
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Notes. Some of the hypotheses could have been worded more clearly. For the sake of transparency, we have reproduced our hypotheses here exactly as they appear in our preregistration, except for the addition of some additional explanatory text in square brackets.

*Hypothesis 6 would be clearer with the word “participants” removed.

2 Materials and Methods

2.1 Participants

Replicating the data collection mechanism used in van der Linden et al., we collected data using Amazon Mechanical Turk (MTurk). When writing our preregistration, we planned our sample size based on resource constraints in conjunction with a power analysis. We estimated that the funds we had available for data collection would permit us to collect data from 1,111 participants (approximately 222 per condition) on Mechanical Turk while paying each participant USD0.50, as per the original study. Exchange rate fluctuations meant that we had to downgrade this to a target sample size of 850 by the time data collection commenced.

Our inclusion criteria specified that participants had to have a 99% approval rating and live in the USA (specified as worker requirements on MTurk) and had to be 18 years or older (the minimum age for all MTurk workers). These inclusion criteria mimicked those in van der Linden et al. quite closely, although we used a 99% approval rate cut-off rather than 95% due to a widely-reported spike in poor-quality responses on MTurk around the time of our study (Dreyfuss, 2018). We were able to collect 822 out of the target of 850 participants before Amazon unexpectedly shut down the first researcher's account, inaccurately claiming that we had misrepresented our location.

Our exclusion criteria for collected data were as follows. These were not exactly the same as in the original study, which did not report detailed exclusion criteria, but were specified to deal with issues such as inattentive respondents or participants who stopped responding shortly after opening the survey.

1. Missing 50% or more of the items in the survey. Specifically, participants who missed six or more (50%) of the twelve main items used for the study were excluded; this resulted in the exclusion of 26 participants. (After application

of this rule, there was just one remaining missing value on the outcome variable, which was dealt with by using listwise deletion per analysis).

2. Failing a simple attention check (participants were asked to type “I am paying attention” in a textbox; this did not necessitate any exclusions)
3. Not living in USA (this was specified as an MTurk worker requirement, and also checked via a survey question; this did not necessitate any exclusions)
4. Having the occupation of climate scientist (4 exclusions).

In addition to the criteria specified above, our preregistration also stated that we would remove “multiple responses from identical GPS locations or BOT identified locations” (the latter referring to locations that we discovered to produce many low-quality respondents). We discovered later that this criterion was not appropriate, since the GPS (latitude and longitude) co-ordinates recorded by Qualtrics are only accurate to the city level for most participants. As such, we deviated from the preregistration and did not apply this exclusion criterion.

After the removal of responses meeting our exclusion criteria, the final sample size was $N = 792$ (see Table 4 for cell N s). On the basis of a sensitivity analysis, we calculate that this implies that we had at least 90% power to detect effect sizes of Cohen’s $\delta \geq 0.26$ for the paired t tests (hypotheses 1 to 5) and to detect effect sizes of $f \geq .14$ for the ANCOVA (hypotheses 8 to 12). As such, our study had adequate power to detect moderately small effects for the main hypotheses of interest. However, power for the analyses of hypotheses relating to party affiliation (H6 & H7) was more modest; these analyses had 90% power only to detect effect sizes of $f \geq .29$ (an approximately “medium” effect size). Full participant demographics are displayed in

Table 2 Table 2. See the Supporting Information at <https://osf.io/3rnrf7/> for a more detailed power analysis.

Table 2

Sample Demographic Characteristics

Demographic	Characteristic	Frequency	Percentage
Gender ($n = 791^a$)	Male	451	57.0%
	Female	337	42.6%
	Gender Diverse	3	0.4%
Age ($n = 791$)	18 – 24	59	7.5%
	25 – 44	571	72.2%
	45 – 59	129	16.3%
	60+	32	4.0%
Education ($n = 789$)	School	204	25.9%
	College	453	57.4%
	Masters	92	11.7%
	Doctorate	30	3.8%
	Other	10	1.3%
Party Affiliation ($n = 790$)	Democrats	396	50.1%
	Republicans	152	19.2%
	Independents	231	29.2%
	Other	11	1.4%

Note. ^aSample sizes vary due to some participants missing demographic items. Missing responses excluded from the denominator when calculating percentages.

2.2 Procedure and Measures

An advertisement with a link to the information sheet and survey was distributed through MTurk to recruit participants. To disguise the purpose of the experiment, the information sheet instructed participants that they were being asked about 1 out of 20 possible media topics. In reality, they were all asked about climate change.

The survey was delivered in Qualtrics, and began by asking participants “To the best of your knowledge, what percentage of climate scientists have concluded that human-caused climate change is happening?” (perceived scientific consensus, the dependent variable), with response on a slider with endpoints of 0 and 100%. They were then asked how certain they were of this estimate, on a rating scale with endpoints of 1 (“I am not at all certain”) and 7 (“I am very certain”); this variable was recorded in order to replicate the procedure in van der Linden et al., although it did not have any role in our preregistered analyses. Participants were then randomly allocated into one of the five conditions listed in Table 3, involving the presentation of one or more sets of stimuli. After being administered these stimuli, they were then once again asked what percentage of climate scientists have concluded that human-caused climate change is happening, and how certain they were of their estimates. Finally, they were asked to answer a small set of demographic questions, including which political party they most identified with (Democrats, Republicans, Independents, or Other). After completing the survey, participants were provided with an online debriefing (see the Supporting Information at <https://osf.io/3rnf7/>).

2.4 Ethics Approval

This study received ethical approval from the Massey University Human Ethics Committee, Northern.

Table 3

Experimental Conditions

Condition	Condition name	Description
1	Control	Participants solved a word puzzle
2	Consensus-treatment	Participants were exposed to a pie chart with text stating 97% of climate scientists have concluded that human-caused climate change is happening
3	Counter-message	Participants were exposed to an image of the Oregon petition rejecting the existence of anthropogenic global warming, with text stating 31,487 American scientists have signed this petition.
4	Consensus-treatment followed by counter-message	Participants were exposed to the stimulus from Condition 1 (consensus-treatment) and then the stimulus from Condition 2 (counter-message)
5	Consensus-treatment + inoculation followed by counter-message	Participants were exposed to the stimulus from Condition 2 (consensus-treatment), then an inoculation message warning them about the existence of politically motivated misinformation (and problems with the Oregon petition in specific), then the stimulus from Condition 3 (counter-message).

Note. The full stimulus materials are available in the electronic Supporting Information at

<https://osf.io/3rnf7/>.

2.2.1 Deviation from original counter-message stimuli

In van der Linden et al.'s main study (Study 2), an image of the Oregon petition was used "as the main counter-message" (p. 3), and this stimulus was likewise used in the counter-message condition in our study. However, we learned during the review process that, in van der Linden et al. (2017), a written statement was included before the image. This statement was a short paragraph describing how many scientists had signed the Oregon petition, beginning with the sentence "There is no consensus among scientists about climate change". This statement had been one of six that a separate sample of participants had ranked for familiarity and persuasiveness (Study 1 in van der Linden et al., 2017), with this statement ranking highest on familiarity and persuasiveness. We had not included this statement in our counter-message condition, as it was not included in the set of stimuli in the Supplementary Information for Study 2 (their main study). The possibility of its inclusion in their main study was raised by a peer reviewer and confirmed by Dr van Linden. Our counter-message condition thus differed from that in the original study in that it included only the Oregon petition image, and not the preceding statement.

3 Results

3.1 Within-Subjects Hypotheses

The within-subjects mean differences in perceived scientific consensus were analysed using paired t tests (see Table 4 and Figure 1). Hypotheses 1 (no change in the control condition), 2 (increased perceived scientific consensus in the consensus-treatment condition), 3 (decreased perceived scientific consensus in the counter-message condition) and 5 (increased perceived scientific consensus in the inoculation condition) were supported. On the other hand, Hypothesis 4 (no change from pretest to posttest amongst participants who received both the consensus-treatment stimulus and the counter-message) was not supported; participants in this condition showed an increase in perceived scientific consensus from pretest to posttest.

Table 4

Pretest and Posttest Means by Condition for Perceived Scientific Consensus

Experimental Conditions	Hypothesised difference	Pretest $M (SD)$	Posttest $M (SD)$	M_{diff}	d^*	p
1: Control ($n = 158$)	No change (H1)	82.08 (18.00)	81.36 (18.55)	-0.72	-0.04	.122
2: Consensus-treatment ($n = 161$)	Posttest higher (H2)	83.08 (15.78)	94.09 (9.68)	11.01	0.70	<.001
3: Counter-message ($n = 158$)	Posttest lower (H3)	80.96 (19.87)	75.96 (24.79)	-5.01	-0.25	<.001

4: Consensus-treatment, counter-message ($n = 156$)	No change (H4)	83.45 (17.09)	92.82 (12.89)	9.37	0.55	<.001
5: Consensus-treatment, inoculation, counter- message ($n = 158$)	Posttest higher (H5)	83.35 (15.67)	93.96 (13.49)	10.61	0.68	<.001

Note. *Denominator of Cohen's d calculation = pretest SD.

Figure 1. Mean difference between posttest and pretest perceived scientific consensus by condition. CT = Consensus-treatment. CM = counter-message. Inoc = Inoculation. Error bars depict 95% confidence intervals.

3.2 Political Affiliation Hypotheses

Mean pretest-posttest differences in perceived scientific consensus within each condition and party are displayed in Table 5. In our preregistration, we inadvertently neglected to specify which data analyses we would use to test hypotheses 6 and 7. The data analyses we ultimately used to test these hypotheses are detailed below. However, the analysis method we have selected is just one of several ways that one might reasonably use our data to test these two hypotheses. Other researchers might wish to apply other methods using our open data at <https://osf.io/8ymj6/>. Participants who did not provide their party affiliations or provided their party affiliation as “Other” were excluded from these analyses.

3.2.1 Hypothesis 6

We tested hypothesis 6 (that the consensus-treatment would have a larger effect for those who identify as Republicans and Independents than it would for Democrats) by calculating the posttest-pretest differences in perceived scientific consensus ratings for participants in the consensus-treatment condition (condition 2), and then using these differences as the dependent variable in an ANOVA with political party affiliation (Republican, Independent or Democrat) as the independent variable. This ANOVA did not indicate any significant main effect, $F(2, 156) = 2.43, p = .092, \eta^2 = .03$, meaning that hypothesis 6 was not supported.

3.2.2 Hypothesis 7

Hypothesis 7 predicted that the change in perceived scientific consensus in condition 4 (consensus-treatment + counter-message) would be more negative for Republicans than Democrats or Independents. We similarly tested this hypothesis by calculating the posttest-pretest differences in perceived scientific consensus ratings for participants in condition 4 and

then using these differences as the dependent variable in an ANOVA with political party affiliation as the independent variable. This analysis did suggest a main effect of political affiliation, $F(2, 151) = 6.09, p = .003, \eta^2 = .08$. However, the pre-post difference scores for Republicans were not significantly different from those of Independents $M_{diff} = -5.73, p = .158, d = -0.31$, or Democrats, $M_{diff} = 5.99, p = .105, d = 0.36$. As such, hypothesis 7 was not supported.

Table 5

Mean Differences in Perceived Scientific Consensus (Posttest – Pretest) by Political Party Affiliation

	Democrat ($n = 395^a$)			Republican ($n = 152$)			Independent ($n = 231$)		
Condition	n	M	SD	n	M	SD	n	M	SD
1: Control	88	-1.30	6.13	29	0.52	6.61	37	-0.16	4.25
2: CT	78	8.71	12.88	37	15.89	25.45	44	10.43	11.75
3: CM	73	-3.96	12.54	25	-10.76	19.11	56	-2.71	10.75
4: CT CM	74	4.61	17.12	35	10.60	15.09	45	16.33	20.98
5: CT Inoc CM	82	8.71	16.57	26	13.23	17.87	49	12.27	17.93

Note. One participant (who identified as a Democrat) had missing data on the post-measurement of perceived scientific consensus, and was excluded in this analysis.

3.3 Between-Condition Hypotheses

As preregistered, Hypotheses 8 to 12 were tested by estimating a single ANCOVA model in which posttest perceived scientific consensus score was the dependent variable, condition was the independent variable, and pretest perceived scientific consensus score was

the covariate. The ANCOVA revealed a significant main effect of condition, $F(4, 785) = 54.92, p < .001, \eta_p^2 = .22$. This was then followed up by a set of pairwise comparisons of estimated marginal means (one pairwise comparison to test each of hypotheses 8 to 12). The estimated marginal means are the posttest means that have been adjusted for pretest differences between the groups. As indicated in our preregistration, no correction for familywise Type I error rates was employed in these comparisons, given that we were deliberately focusing on a restricted set of comparisons where there was a strong basis to expect the presence of effects.

3.3.1 Hypothesis 8

Hypothesis 8 predicted that participants in condition 2 (consensus-treatment) would have significantly higher posttest levels of perceived scientific consensus than participants in condition 1 (control group), when controlling for differences in pretest scores. Hypothesis 8 was supported, with a higher adjusted posttest mean perceived scientific consensus in the consensus-treatment condition, $M_{diff} = 12.14, p > .001, 95\% \text{ CI } [9.22, 15.06]$. The Cohen's d effect size for this difference (using the pretest standard deviation across all participants in all conditions as the denominator) was 0.70.

3.3.2 Hypothesis 9

Hypothesis 9 predicted that participants in condition 3 (counter-message) would have significantly lower posttest levels of perceived scientific consensus than participants in condition 2 (consensus-treatment), when controlling for differences in pretest scores. A pairwise comparison of estimated marginal means showed hypothesis 9 was supported, $M_{diff} = -16.89, p < .001, 95\% \text{ CI } [-19.81, -13.97], d = 0.97$.

3.3.3 Hypothesis 10

Hypothesis 10 predicted that participants in Condition 5 (consensus-treatment, inoculation, counter-message) would have significantly higher posttest levels of perceived scientific consensus than participants in condition 4 (consensus-treatment, counter message), when controlling for differences in pretest scores. Hypothesis 10 was not supported, $M_{diff} = 1.19$, $p = .426$, 95% CI [-1.75, 4.14], $d = 0.07$.

3.3.4 Hypothesis 11

Hypothesis 11 predicted that participants in condition 2 (participants receiving a consensus message only) would have significantly higher posttest levels of perceived scientific than participants in condition 4 (participants receiving a consensus and counter-message), when controlling for differences in pretest scores. Hypothesis 11 was not supported, $M_{diff} = 1.49$, $p = .318$, 95% CI [-1.44, 4.42], $d = 0.09$.

3.3.5 Hypothesis 12

Hypothesis 12 predicted that participants in condition 3 (counter-message only), would have significantly lower posttest levels of perceived scientific consensus than participants in condition 5 (consensus-treatment, inoculation, counter-message), when controlling for differences in pretest scores. Hypothesis 12 was supported, $M_{diff} = -16.60$, $p < .001$, 95% CI [-19.53, -13.67], $d = -.96$. An additional exploratory (non-preregistered) analysis indicated that the difference between Condition 5 and Condition 1 (control) was also statistically significant, $M_{diff} = 11.85$, $p < .001$, 95% CI [8.92, 14.78], $d = 0.68$.

4 Discussion

Overall, our attempt to replicate van der Linden et al (2017) produced mixed findings: Specifically, seven of our twelve hypotheses based on van der Linden et al.'s (2017) original study were supported. Of course, this does not definitively indicate that the unsupported hypotheses are in fact false: No single study can conclusively establish the presence or absence of an effect. Furthermore, a particular relationship being statistically significant in one study and not in another does not necessarily imply that the two studies have produced significantly different estimates (Gelman & Stern, 2006). Our study did not attempt to quantitatively determine whether the effect size estimates in our study are inconsistent with those in the original study (see for example the methods in Verhagen & Wagenmakers, 2014). Other researchers may wish to attempt such comparisons using our open data.

We were able to replicate the finding that communicating information about the scientific consensus on human-caused climate change can increase public perception to align with scientific consensus more closely (H2, H8). This effect was quite large: The pretest-posttest comparison of the effect of exposure to information about the scientific consensus indicated a mean increase in perceived scientific consensus of 11% or $d = 0.70$ (a Cohen's d of 0.8 is typically regarded as a large effect; Cohen, 1988). That said, these effects were not quite so large as in van der Linden et al., who reported a Cohen's d of 1.23 for the pretest posttest comparison in their consensus-treatment group. We also found that exposure to misinformation decreased the perceived scientific consensus on climate change (H3), although at $d = -0.25$ this effect was again smaller than the $d = -0.48$ reported by van der Linden et al. While our findings pertain only to participants' beliefs about scientific consensus rather than their own beliefs about climate change, there is some evidence that increasing perceptions of scientific consensus on climate change can increase personal agreement that climate change is occurring (van der Linden et al., 2015, 2019).

To the extent that we were unable to replicate some of van der Linden et al.'s findings these problems seemed to relate especially to condition 4 (consensus-treatment + counter-message). Participants in this condition displayed an increase in their perception of scientific consensus on climate change, rather than the predicted no change (H4). This suggests that the positive effect of the consensus-treatment overwhelmed the relatively small negative effect of the counter-message. Admittedly, the fact that van der Linden et al. did not find a significant pretest-posttest difference in this condition may not have been an especially strong basis for our hypothesis of no change between pretest and posttest in this condition (H4), and H4 itself was of relatively limited importance in our study. However, several other hypotheses (H7, H10, and H11) related to comparisons involving condition 4, and none of these hypotheses were supported. Most crucially, hypothesis 10 (that participants receiving a consensus-treatment, an inoculation, and then a counter-message would display higher levels of perceived scientific consensus than those simply receiving a consensus-treatment and then a counter-message) was not supported. It was the test of this hypothesis that comprised the strongest test of the effectiveness of the inoculation intervention. While it appeared that the inoculation provided a substantial benefit in comparison to a pure counter-message (H12), we are unable to conclude that the inoculation intervention provides an additional benefit beyond the simple consensus-treatment intervention (i.e., telling participants about the percentage of scientists who agree that climate change is occurring due to human activities). This finding is similar to that in Cook et al. (2017). That said, the high level of perceived scientific consensus in condition 4 (93%, being near the maximum of 100%) means that a ceiling effect is likely to have been present in our study: This meant that the capacity for the inoculation intervention to exert an additional effect beyond that of the consensus-treatment was limited. A similar ceiling effect may have occurred in Cook et al. (2017, Study 1); their misinformation manipulation had an effect that was also small, being virtually identical in

size to that found in our study (a reduction in perceived scientific consensus relative to the control condition of 5.4%).

There are several potential explanations for the relatively small effect of the counter-message in our study, and by extension the high level of perceived scientific consensus observed in condition 4 (consensus-treatment + counter-message). One possibility is that not all participants read the counter-message properly, thus reducing its effect on perceived scientific consensus, and reducing our capacity to determine whether the inoculation buffered the effect of the counter-message to a greater extent than the consensus-treatment did. This explanation is plausible because the counter-message (an image of the Oregon petition) was presented in the form of an image file (as was the case in the original study), and the text on this image could have been difficult to read for some participants—especially those viewing the survey on mobile phones. This problem may have been further aggravated by the fact that the Oregon petition image we used was taken from the (pdf) Supporting Information file of van der Linden et al. (2017), which may have been subject to some loss of resolution when embedding in a pdf document. This implies that the image displayed to van der Linden et al.’s participants may have been of greater resolution than the one used in our study. As noted earlier, van der Linden et al. also included a text misinformation statement (see section 2.2.1) along with the Oregon petition image, which would presumably have been easy for all participants to read. These factors may explain the stronger effect of the counter-message in van der Linden et al.’s study in comparison to ours. This potential dependence of our findings on idiosyncratic features of the experimental stimuli speak to the presence of substantial uncertainty about the degree to which our findings can be generalized to other stimuli, such as other items of misinformation (see also Yarkoni, 2019).

Another potential explanation for the high level of perceived scientific consensus in condition 4 is that many participants in our sample already had high levels of belief in the

reality of climate change, and may have been unwilling to be persuaded by a counter-message. Indeed, the *pretest* levels of perceived scientific consensus were relatively high in this study—about 80% in all conditions, and around 10% higher in each condition than in van der Linden et al.

4.1 Limitations

Our study shared some limitations of the original. For example, data for both studies were obtained from online convenience samples from the US; as such, the findings cannot confidently be assumed to hold for the general US population, nor the general human population. The findings may not necessarily generalise to other samples and contexts, and replications with more diverse samples (e.g., not restricted to MTurk workers in the USA) may be valuable. Both our study and van der Linden et al.'s were also brief computerised experiments; we did not examine the persistence of effects of the manipulations of perceived scientific consensus over time. Nor did we examine how the manipulations affected participants' own beliefs about climate change, or any downstream behavioural effects (see Nilsson, Fielding, & Dean, 2020).

Our study also had some specific limitations as a replication. Our study was preregistered, but some details were missing in this preregistration (e.g., the analysis method for hypotheses 6 and 7), we deviated from the preregistration after discovering that one of our exclusion criteria was inappropriate, and the stimuli used in our counter-message condition differed from those used in the original study (as discussed above). The sample size of our study, while large, was not as large as that in van der Linden et al.'s original study (which had $N = 2,167$). While we had very high power (>99%) to detect effects of the size reported in the original study for most of the hypotheses (see the Supporting Information at

<https://osf.io/3rnf7/>), this was not the case for the hypotheses relating to political affiliation, H6 and H7, which involved smaller subgroups of the sample.

4.2 Conclusion

In conclusion, our findings suggest that while misinformation does reduce perceptions of scientific consensus about climate change, exposing participants to more accurate information about scientific consensus can be effective in countering the impact of this misinformation. This reinforces the message that there is value in addressing and countering misinformation in the public sphere (rather than avoiding mentioning misinformation for fear of provoking “backfire effects”; see Wood & Porter, 2019). What is less clear, however, is whether an “inoculation” intervention is more effective than simply providing information about scientific consensus. We were unable to replicate van der Linden et al.’s (2017) finding of an added benefit of inoculation (albeit that a potentially ceiling effect might partially explain our finding in this regard). Further research may be needed to reduce uncertainty around the added benefit of inoculation.

5 References

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