Supplementary information

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A 27-country test of communicating the scientific consensus on climate change

In the format provided by the authors and unedited

Supplementary Information

1. Design Table

Supplementary Table 1: Overview of RQs, Hypotheses, and the Pre-Registered Sampling, Analytic, and Interpretation Plan (Prior to Data Collection but not Submitted as a Registered Report)

2. Supplementary Results

2.1. Summary of the Frequentist Random-Effects Meta-Analytic Models

Supplementary Table 2

Note. d refers to the estimated meta-analytic Cohen's *d*. The numbers in brackets indicate the 95% confidence interval. τ_c refers to the estimated meta-analytic heterogeneity across countries.

2.2. Percentages of Participants per Country That Underestimate the Reality Consensus and Crisis Agreement

Supplementary Table 3

Note. The numbers in brackets indicate the 95% confidence interval.

2.3. Comparison Between Control and Updated Conditions

We examined the effects of the updated consensus message on reality consensus and crisis agreement perceptions, climate change beliefs (reality and human-causation), worry, and policy support compared to the control condition.

Besides the results described in the main text, we find that the effects on climate change beliefs (H2_c and H2_d), worry (H2f), and support for public action (H2_g) of the updated condition are consistent with those of the classic condition.

In terms of climate change beliefs (H2_c and H2_d), we find extremely strong (BF₊₀ = 131.63) and very strong ($BF_{+0} = 69.86$) support that people believe more in climate change and human activity as its main cause after being exposed to the updated compared to the control message. Both intervention effects are small (reality: Cohen's *d* = 0.07, 95% CI [0.02, 0.12]; human-causation: Cohen's *d* = 0.09 [0.04, 0.15]), but consistent across the 27 studied countries (reality: $BF_{10} = 3.45 \times 10^{-6}$, $\tau_c = 0.04$, 95% CI [0.00, 0.14]; human causation: $BF_{10} =$ 5.45x10⁻⁵, τ_c = 0.07, 95% CI [0.00, 0.16]). However, there is only weak evidence for an effect of the updated scientific consensus intervention on climate change worry (H2 $_f$) across countries (BF+0 = 2.05; Cohen's *d* = 0.04, 95% CI [-0.01, 0.08]; between-country heterogeneity: $BF_{10} = 2.53 \times 10^{-11}$, $\tau_c = 0$ [0, 0.08]). In contrast to H2_g, the evidence for an effect of the updated scientific consensus message on climate policy support is consistently weak across the 27 countries (BF+0 = 0.65, Cohen's *d* = 0.02 [-0.02, 0.07]; between-country heterogeneity: $BF_{10} = 1.83 \times 10^{-9}$, $\tau_c = 0$, 95% CI [0, 0.07]).

We also explored effects on confidence in agreement perceptions. We find extremely strong exploratory evidence that participants are more confident in their agreement perceptions after seeing the updated compared to the control message (not preregistered; $BF_{10} =$ 8.42×10¹⁴; Cohen's *d* = 0.76; 95% CI [0.70, 0.79]; between-country heterogeneity: BF₁₀ = 5.81, τ_c = 0.10, 95% CI [0.03, 0.20]).

2.4. Three-Way Interaction Effects Between Political Ideology/Trust in Scientists, Condition, and Pre-Intervention Consensus/Agreement Perceptions

Perceived Scientific Consensus (pre-intervention) *Note.* The lines represent means and the shaded bands represent the 95% confidence intervals.

Note. The lines represent means and the shaded bands represent the 95% confidence intervals.

2.5. Main Analyses Robustness Checks (Without Demographic Covariates)

perceptions moderated by political ideology?

2.6. Exploratory Analyses of Country-Level Collectivism and Power Distance as Potential Moderators of Intervention Effectiveness

Analogous with the confirmatory moderation analyses, we used Bayesian mixed-effects linear regressions, with participants (level 1) nested in countries (level 2) and controlling for relevant demographic characteristics (i.e. age, gender, university degree, and political ideology). All model configurations were identical to confirmatory models.

For the classic consensus message, we find moderate and strong evidence against any moderation of the effect on consensus perceptions by individualism-collectivism (BF₁₀ = 0.20; *b* = -0.05, 95% CI [-0.11, 0.01]) and power distance (BF₁₀ = 0.08; *b* = 0.03, 95% CI [-0.03, 0.10]) respectively. This was also the case for the updated consensus message: we find moderate evidence against a moderation by individualism-collectivism ($BF_{10} = 0.18$, $b = -$ 0.04, 95% CI [-0.10, 0.02]) and power distance (BF₁₀ = 0.16, *b* = 0.05, 95% CI [-0.01, 0.11]) on consensus perceptions. For agreement perceptions changes in the updated (vs. control) condition, the results are inconclusive, with weak evidence against a moderation by individualism-collectivism (BF₁₀ = 0.35, b = -0.07, 95% CI [-0.15, 0.02]) and weak evidence for a moderation by power distance (BF₁₀ = 1.53, *b* = 0.08, 95% CI [0.02, 0.15]).

3. Supplementary Methods

3.1. Population Statistics Per Country

Supplementary Table 5

Note. References:

¹ United Nations Data Portal (2023). *Median Age of Population.*

https://population.un.org/dataportal/data/indicators/67/locations/32/start/1990/end/2023/table/pivotbylocation ² The World Bank (2023). *Population, female (% of total population).*

https://data.worldbank.org/indicator/SP.POP.TOTL.FE.ZS.

³ The World Bank (2023). *Educational Attainment, at least completed post-secondary, population 25+.*

https://data.worldbank.org/indicator/SE.SEC.CUAT.PO.ZS?end=2020&most_recent_value_desc=true&start=1970&view=cha rt

⁴ The World Bank (2023). Urban population (% of total population).

https://data.worldbank.org/indicator/SP.URB.TOTL.IN.ZS?end=2022&start=1960&view=chart

⁵ OECD (2023). *Adult education level.* https://data.oecd.org/eduatt/adult-education-level.htm#indicator-chart 6 IBG Educa (2023). *Conheça o Brasil - População Educação.* https://educa.ibge.gov.br/jovens/conheca-obrasil/populacao/18317-

educacao.html#:~:text=N%C3%ADvel%20de%20Instru%C3%A7%C3%A3o&text=No%20Brasil%2C%2053%2C2%25,%2C2%25 %20no%20mesmo%20ano.

⁷ OECD GPS Education (2023). *Education at a Glance 2022 (EAG 2022): Highlights.*

https://gpseducation.oecd.org/IndicatorExplorer?plotter=h5&query=22

⁸ GEOSTAT (2023). *Population.* https://www.geostat.ge/en/modules/categories/41/population

⁹ Population Reference Bureau (2023). *Percent of Population Living in Urban Areas.*

https://www.prb.org/international/indicator/urban/snapshot

¹⁰ Centraal Bureau voor de Statistiek (2023). https://www.cbs.nl/

¹¹ Republika Slovenija Statistični Urad (2023). https://www.stat.si/statweb

¹² Statistikmyndigheten (2023). https://www.scb.se/

¹³ Turkish Statistical Institute (2023). *National Education Statistics, 2022.* https://data.tuik.gov.tr/Bulten/Index?p=Ulusal-Egitim-Istatistikleri-2022-49756

3.2. Procedure Outline

Supplementary Figure 2

Note. This is a depiction of the order (from top to bottom) in which study materials (i.e., measures and the messaging intervention) were shown to all participants.

3.3. Updated Consensus Wording Choice

The wording of the scientific crisis agreement message is based on the *Nature* survey of IPCC 6 authors¹. Albeit this quantification of the crisis agreement among scientists has not been obtained in the same way the 97-99% consensus on the reality of climate change (i.e., through a review of peer-reviewed climate science research), we opted for a numerical quantifier of the agreement on the urgency of climate change to maintain consistency between the format of the two statements. We did so because a statement communicating

unquantified high scientific confidence in climate change risks and the need for immediate action (e.g., see IPCC Working Group II headline statements^{[21](https://www.ipcc.ch/report/ar6/wg2/resources/spm-headline-statements)}) might not be as persuasive compared to the explicitly quantified consensus on the reality of climate change. This is especially critical when the two statements are shown as one message and therefore open to direct comparisons by participants. This is further corroborated by findings showing the numeric (i.e., more precise), as opposed to verbal (i.e., less precise), message on the scientific consensus on the reality of climate change is generally more effective in increasing perceived consensus².

3.4. Pilot Study

We conducted a pilot study among 395 US-American participants to test the wording of the updated consensus message—a combined message that communicated both the scientific agreement on climate change as a crisis (i.e., '88% of climate scientists agree that climate change constitutes a crisis') and the scientific consensus on the reality of climate change (i.e., 97% of climate scientists agree that human-caused climate change is happening'). We tested this message against two other messages: a message that only communicated the scientific agreement that climate change constitutes a crisis and the 'classic' consensus message. The pilot also served to derive estimates for the data simulation as part of the Bayesian design analysis (i.e., the correlation between pre-post-intervention measurements; how the upper bound affects the residual variance in the intervention conditions; how the interventions influence the pre-post-intervention correlations; see Analysis plan for more information).

Procedure

In this pilot study, we used the same procedure and materials as described in this Registered Report, except that the pilot was run on a paid US sample on Prolific (February 10, 2023). Due to resource constraints, we merged these data with a control condition (i.e., '97% of dentists recommend brushing your teeth twice a day') data from a previous pilot study conducted on Prolific with a US sample (February 2-3, 2023).

Participants

After filtering and excluding inattentive participants, the final sample included 395 US-American participants (*M* = 38.01 years, *SD* = 13.55; 47.34% female). Most of them were employed full-time (52.15%), White (71.29%), and had a slightly below average, average, or slightly above average income.

Results

In Supplementary Table 5, we report descriptive statistics, including means and standard deviations, of all outcomes. The results of the pilot study (*N* = 395) provide initial, descriptive evidence that the updated message that emphasizes both the scientific consensus on the reality of climate change and agreement on climate change as a crisis may increase all outcomes compared to the control condition, as well as boost worry and support for public action more than the classic scientific consensus message. On the other hand, the updated message that communicates only the scientific crisis agreement seems to reduce belief in climate change and its human causation, worry, as well as support for action compared to all other conditions. This suggests that communicating scientists' perceptions of climate change as a crisis, in the absence of the 97% consensus on the reality of climate change, is likely not an effective message for public climate change communication efforts. Based on these initial results, we selected the combined message for the main confirmatory study.

Supplementary Table 6: Descriptive Statistics for Each Outcome per Experimental Condition

Note. Control = '97% of dentists recommend brushing your teeth twice per day'; Classic = '97% of climate scientists agree that human-caused climate change is happening'; Crisis only = '88% of climate scientists agree that climate change is a crisis'; Updated = Classic + Crisis. As the control condition is from another pilot study, scientific agreement pre- and post-intervention, as well as belief in climate change as a crisis are missing.

3.5. Country-Specific Instrument Adaptations

The following table describes all major contextual considerations and adaptations to the survey instrument. All adaptations were approved by the two lead authors. Example adaptations include clarifying what is meant with left and right in the political ideology item, adding the English term "climate change" in parenthesis after the term in the local language, and adding "you yourself/you personally" to clarify that the item asks about an individual's opinion.

Supplementary Table 7

3.6. Overview of the Analytical Approach

General overview of Bayesian hypothesis testing and Bayesian model averaging

We base our analyses on Bayesian hypothesis testing and Bayesian model-averaging frameworks^{3–5}. Bayesian hypothesis testing uses Bayes factors,

$$
BF_{10} = \frac{p(H_1|data)}{p(H_0|data)} / \frac{p(H_1)}{p(H_0)}
$$

to quantify the evidence in favor of the alternative (H_1) vs. the null (H_0) hypothesis (as a change from prior to posterior odds). Bayes factors are a continuous measure of evidence that quantifies how likely the data are under each of the hypotheses, with $BF_{10} > 1$ showing support for the alternative hypothesis and BF_{10} < 1 showing support for the null hypothesis^{6,7}. We will use the conventional labels when referring to the degree of evidence for each hypothesis, i.e., Bayes factors between 1 and 3 (between 1 and 1/3) are considered weak evidence, Bayes factors between 3 and 10 (between 1/3 and 1/10) are considered moderate evidence, and Bayes factors larger than 10 (1/10) are considered strong evidence in favor of (against) a hypothesis^{8,9}.

Bayesian model-averaging extends Bayesian hypothesis testing to multi-model settings. This allows for incorporating uncertainty about the specified models into the analyses and for drawing more robust conclusions¹⁰. Throughout the analysis, we will specify different null and the alternative hypotheses via sets of models (H₀: M₀₁, ..., M_{0A}, H₁: M₁₁, ..., M_{1B}, respectively). In such settings, we use inclusion Bayes factors,

$$
BF_{10} = \frac{\sum_{b=1}^{B} p(M_{1b}|data)}{\sum_{a=1}^{A} p(M_{0a}|data)} / \frac{\sum_{b=1}^{B} p(M_{1b})}{\sum_{a=1}^{A} p(M_{0a})'}
$$

which extend regular Bayes factors to multi-model settings (with the same interpretation– therefore the same abbreviation $4,11$.

Overview of the hypothesis testing approach

Prior to conducting this study, we have four confirmatory and two planned exploratory research questions that pertain to the broad study aims (see Table 1). Throughout the analysis, we perform a series of multiple two-group comparisons, comparing either the control and the consensus condition, the control and the updated consensus condition, or the consensus and the updated consensus condition. This also facilitates conclusions about both intervention messages separately. Our outcome variables can be split into two categories: 1) *continuous outcomes,* consisting of perceived scientific consensus (on the reality of climate change) and perceived scientific agreement (on climate change as a crisis), measured on a 0%–100% scale and 2) *ordinal outcomes,* consisting of belief in the reality of climate change, belief in the human causation of climate change, belief in climate change as a crisis, climate change worry, and support for public action measured on 7-point Likert scales. Since all continuous outcomes and all ordinal outcomes use the same model specifications, we describe the analytic plan for the hypotheses regarding continuous outcomes (i.e., consensus and agreement perception) jointly, and we do the same for all ordinal outcomes (i.e., belief in climate change, belief in human causation, belief in climate change as a crisis, climate change worry, and support for public action), in the corresponding sections (see Table 1 for mapping between hypotheses, group comparisons, and outcomes).

For consensus and agreement perception (i.e., continuous outcomes), we also conduct a moderation test to assess whether the intervention effect is modified by one of the moderators: familiarity with consensus/agreement messages, trust in climate scientists, and political ideology.

In all analyses, we will adjust for the following covariates: age (continuous), gender (categorical), education (dichotomized into no university degree vs. university degree), and political orientation (continuous). For all tests except the moderation by political ideology, we specify a directional alternative hypothesis.

Besides the specified hypotheses tests, we will report standardized mean differences between all groups for all outcomes (regardless of whether the outcome variable is continuous or ordinal), to facilitate incorporating the results into future meta-analyses. For moderation analyses, we will report standardized regression coefficients of the interaction effect. To make the results readily available for any future country-specific evidence synthesis, we will also report by-country specific standardized mean effect sizes and standardized regression coefficients in a supplementary table.

Bayes factor design analysis

We perform Bayes factor design analysis (BFDA) to evaluate the performance of our models $12,13$. In each BFDA, we examine model performance when simulating data from the null hypothesis of no effect and the alternative hypothesis assuming the presence of the effect. Under the presence of the effect, we consider two scenarios: a scenario based on previous findings (i.e., "empirical"), assuming the presence of the effect corresponding to effect sizes reported in previous meta-analyses^{14,15} and a pessimistic scenario assuming the presence of an effect half the size.

In all scenarios, we further expand the BFDA set-up to examine the performance of the models under no heterogeneity, substantial heterogeneity, and excessive heterogeneity of the effect across countries (we always assume that countries differ in their baseline measurement, i.e., random intercepts). Consequently, our BFDA settings evaluate model performance across a wide range of conditions, including a robustness check for extremely unfavorable conditions (i.e., lower than expected effect size and excessive heterogeneity). In all BFDAs, we use an expected sample size of 10,000 participants spread equally across the three conditions and 25 countries. Consequently, each of the two-group comparisons is based on 6,666 participants. The number of participants and countries is based on resource and feasibility considerations (i.e., the data collection period is limited due to the collaborators' availability, and funding for data collection is currently limited to \$1,000) and guided by previous experience in similar data collection efforts^{16,17}. Due to computational constraints, each BFDA setting was reproduced 1,000 times, resulting in simulation error of the BFDA BFs classification estimates lower than $1.6\%^{10}$.

Analytic plan for the hypotheses

Continuous outcomes. This subsection describes hypothesis tests evaluating the effects of the classic and updated consensus message on consensus and agreement perceptions (H_{1a} , H_{2a}, and H_{2b}). Please refer to the "Continuous outcomes" section in Supplementary Materials on OSF [\(https://osf.io/udyvj?view_only=08f15cbdca5d41e7ad1c7fa159276c1\)](https://osf.io/udyvj?view_only=08f15cbdca5d41e7ad1c7fa159276c1) for details on the model parameterization and the Bayes factor design analysis.

Models

We will test H_{1a} (control vs. classic: consensus perceptions), H_{2a} (control vs. updated: consensus perceptions), and H_{2b} (control vs. updated: agreement perceptions) using Bayesian mixed-effects linear regression models, with participants at level 1 and countries at level 2. In all models, we will control for the pre-treatment measurement of the consensus/agreement perceptions. The hypothesis test will be performed by comparing two sets of models: a) models specifying the null hypothesis assuming the regression coefficient of the group difference is equal to 0 ($\beta_{\text{group}} = 0$) and b) models specifying the alternative hypothesis assuming the regression coefficient of the group difference is positive and distributed according to a prior distribution f (βgroup ~ *f*()). Each model set, i.e., models a and b, is represented via two models: 1) a model assuming no differences across countries in the group effect (τ_{group} = 0; random intercept only model) and 2) a model assuming differences across countries in the group effect ($\tau_{\text{group}} = g()$; random intercept and random slope model).

We will estimate the models using the *BayesFactor* R package¹⁸. We will use a set prior scale of *r* = 0.50 for the fixed-effects regression coefficients, the "medium" prior scale closely corresponding to the previously reported meta-analytic effect of *g* = 0.55¹⁴ and *r* = 0.25 for the random-effects regression coefficients, assuming that the between-country variability will be approximately half the effect size. The common intercept and residual variance use the default Jeffreys prior.

Hypothesis test

-

Each hypothesis is then evaluated by comparing the alternative hypothesis models (i.e., positive group difference) without (M_{b1}) and with (M_{b2}) between-country heterogeneity to the null hypothesis models (i.e., no group difference) without (M_{a1}) and with (M_{a2}) betweencountry heterogeneity using inclusion Bayes factors.

Bayes factor design analysis

We used standardized mean differences (Cohen's *d*) to define the simulation settings for continuous outcomes. We simulated data under the null hypothesis of no effect (*d* = 0)*,* an empirical alternative hypothesis *(d* = 0.50; a slightly lower effect size than was reported in a recent meta-analysis: Hedges' $q = 0.55^{14}$), and a pessimistic alternative hypothesis ($d = 0.25$; half the effect size of the empirical alternative hypothesis). For heterogeneity in effect sizes, we considered no heterogeneity ($\tau_{\text{group}} = 0$), substantial heterogeneity assuming the standard deviation of true effects is half the effect size (τ_{group} = 0.25), i.e., the maximum amount of heterogeneity we could observe while keeping approximately 97.5% of the country specific effects still positive¹, and extreme heterogeneity assuming the standard deviation of true effects equals the effect size (τ_{group} = 0.50), i.e., almost 15.9% of the effect sizes are in the opposite direction than the mean. We based auxiliary simulation parameters such as the pre-treatment means, pre- and post- treatment residual variances, and pre-post treatment correlations on a pilot study (see Supplementary Information B).

Supplementary Fig. 2 visualizes the proportion of Bayes factors resulting in strong evidence for the alternative hypothesis under the BFDA conditions of primary interests: the null and

 1 These are very conservative settings, given that the previously mentioned meta-analysis reported heterogeneity estimate 1.8 times lower (τ = 0.139)²⁴.

alternative hypotheses under the no and substantial heterogeneity. We verify that the specified tests provide strong evidence $BF_{10} > 10$ for the alternative hypothesis in both heterogeneity conditions under the alternative hypothesis (in all cases under no heterogeneity and in 99.4% of cases under substantial heterogeneity). Furthermore, the specified tests provide strong evidence for the null hypothesis BF_{10} < $1/10$ in 90.9% of the no heterogeneity condition. It should be noted that, in case of substantial heterogeneity, inferences about the absence of the effect are more challenging, and the test can provide strong evidence for the absence of the effect only in the minority of the cases (5.0%).

The robustness check under unfavorable conditions, i.e., half of the expected effect size, excessive heterogeneity, or both, show that while the specified tests are considerably less powerful, they rarely produce misleading evidence. We almost never find misleading evidence for the null hypothesis (BF₁₀ < $1/10$; max. 0.3% under pessimistic alternative hypothesis with excessive heterogeneity) or misleading evidence for the alternative hypothesis (BF₁₀ > 10, max. 0.8% under null hypothesis with excessive heterogeneity). See Table 2 in the Supplementary Materials on OSF for detailed performance estimates under each condition.

Supplementary Fig. 3: Results of Bayes Factor Design Analysis for Continuous Outcomes*.*

Note. The proportion of strong evidence (BF₁₀ > 10; *y*-axis) across different effect sizes (x-axis) and between-country heterogeneity of the effect sizes ("No" = countries differ only in the baseline measure, "Substantial" = countries differ in both the baseline and effect sizes). Results are based on one-sided inclusion Bayes factors from Bayesian model-averaged mixed-effects linear regressions, with no multiple comparison adjustment.

Ordinal outcomes. This subsection describes hypothesis tests evaluating the effects of the classic and updated consensus messages on personal beliefs in the reality of climate change $(H_{1b}$ and H_{2c}), human causation of climate change (H_{1c} and H_{2d}), climate change as a crisis $(H_{2e}$ and H_{3a}), worry $(H_{1d}, H_{2f}$, and H_{3b}), and support for public action $(H_{1e}, H_{2g}$, and H_{3c}). Please refer to the "Ordinal outcomes" section in the Supplementary Materials on OSF for details on the model parameterization and the Bayes factor design analysis.

Models

We will test the hypotheses using Bayesian mixed-effects cumulative probit regression models, with participants at level 1 and countries at level 2. We use the ordinal hypothesis testing framework¹⁹ that allows us to distinguish between different shifts in the ordinal scale response patterns (no, random, constant, and dominant). The hypothesis test will be performed by comparing two sets of models: a) models specifying the null hypothesis assuming the response pattern is either not affected by the treatment or that the response pattern is only randomly affected by the treatment, and b) models specifying the alternative hypothesis assuming the response pattern is either constantly positively affected by the treatment or dominantly positively affected by the treatment. Each model set, i.e., models a and b, is again represented via two models: 1) a model assuming no differences across countries in the group effect ($\tau_{\text{group}} = 0$; random intercept only model) and 2) a model assuming differences across countries in the group effect ($\tau_{\text{group}} = g()$; random intercept and random slope model).

We will estimate the models using *Stan*²⁰ and the *Rstan* R package²¹ and compute the marginal likelihood via bridge sampling using the *bridgesampling* R package²². Based on recent meta-analyses $14,15$, we expect smaller effects of the interventions on the ordinal outcomes than on the continuous outcomes (approximately Cohen's *d* = 0.10). When simulating from models corresponding to the alternative hypotheses, we found that a mean shift in the latent variable θ = 0.14 converts to the Cohen's *d* of approximately 0.10 (if the data were analyzed as continuous). Therefore, we set the standard deviation of the normal prior distribution on group difference in the standard normal latent ability to θ = 0.14 and the standard deviation of the normal distribution for the random effects to τ = 0.07, again assuming that the between-country variability will be approximately half the effect size. The common thresholds use the default standard normal prior distribution 19 .

Hypothesis test

Each hypothesis is then evaluated by comparing the alternative hypothesis models (i.e., positive constant shift differences) without (M_{b1}) and with (M_{b2}) between-country heterogeneity and positive dominant shift differences without (M_{b3}) and with (M_{b4}) between-country heterogeneity to the null hypothesis models (i.e., no differences) without (M_{a1}) and with (M_{a2}) between-country heterogeneity and random shift differences without (Ma3) and with (Ma4) between-country heterogeneity, using inclusion Bayes factors.

Bayes factor design analysis

We used mean differences in the standard normal latent variable (θ) to define the simulation settings for ordinal outcomes. We simulated data under the null hypothesis of no effect (θ = 0)*,* an empirical alternative hypothesis (θ = 0.14; corresponding to an effect size that was reported in recent meta-analyses: $d = 0.10^{14,15}$), and a pessimistic alternative hypothesis (θ = 0.07; half the effect size of the empirical alternative hypothesis). For heterogeneity in effect sizes, we follow the same logic as for the continuous outcomes and consider no heterogeneity ($\tau_{\text{group}} = 0$), substantial heterogeneity assuming the standard deviation of true effects is half the effect size (τ_{group} = 0.07), and extreme heterogeneity assuming the standard deviation of true effects equals the effect size (τ_{group} = 0.14). We specified two common response patterns to verify the performance of our tests under different settings, a centered response pattern where the most common response is in the center of the 7-point Likert scale and a skewed response pattern where the most common response is at the upper bound of the 7-point Likert scale (representing ceiling effects). Since the results did not meaningfully differ between the response patterns, we report the aggregated results.

Supplementary Fig. 3 depicts the proportion of Bayes factors resulting in strong evidence for the alternative hypothesis under the BFDA conditions of primary interests: the null and alternative hypotheses under the no and substantial heterogeneity. We verify that the specified tests provide strong evidence $BF_{10} > 10$ for the alternative hypothesis in majority of the cases in both heterogeneity conditions under the alternative hypothesis (in 90.0% of cases under no heterogeneity and in 86.6% of cases under substantial heterogeneity). Furthermore, the specified tests also often provide strong evidence for the null hypothesis BF¹⁰ < 1/10 (in 51.3% of the no heterogeneity condition and 48.7% cases under substantial heterogeneity). Please refer to Table 5 in the Supplementary Materials on OSF for detailed performance estimates under each condition.

The robustness check under unfavorable conditions (i.e., half of the expected effect size, excessive heterogeneity, or both), shows that the specified tests are less powerful in the substantial or excessive heterogeneity conditions under the pessimistic alternative hypothesis. However, we rarely find misleading evidence for the null hypothesis (BF₁₀ < $1/10$; max. 0.8% under empirical alternative hypothesis with excessive heterogeneity) or misleading evidence for the alternative hypothesis ($BF_{10} > 10$, max. 3.1% under null hypothesis with excessive heterogeneity).

Supplementary Fig. 4: Results of Bayes Factor Design Analysis for Ordinal Outcomes.

Note. The proportion of strong evidence (BF₁₀ > 10; *y*-axis) across different effect sizes (x-axis) and between-country heterogeneity of the effect sizes ("No" = countries differ only in the baseline measure, "Substantial" = countries differ in both the baseline and effect sizes). Results are based on one-sided inclusion Bayes factors from Bayesian model-averaged mixed-effects cumulative probit regression, with no multiple comparison adjustment.

Moderation of continuous outcomes. This subsection describes the hypothesis tests evaluating whether the effectiveness of the classic consensus intervention in changing consensus perceptions is moderated by message familiarity (H_{4a}) , trust in climate scientists (H_{4b}) , as well as political ideology (H_{4c}) . Please refer to the "Moderation" subsection of the "Continuous outcomes" section in the Supplementary Materials on OSF for details on the parameterization of the models and the Bayes factor design analysis.

Models

We will test the hypotheses by extending the Bayesian mixed-effects linear regression models described in the "Continuous outcomes" section with the given moderator and its interaction with the group effect. The hypothesis test will be performed by comparing two sets of models: a) models specifying the null hypothesis assuming the regression coefficient of the interaction between the moderator and the group effect is equal to 0 $(\beta_{\text{moderator*treatment}} = 0)$ and b) models specifying the alternative hypothesis assuming the regression coefficient of the interaction between the moderator and the group effect is positive and distributed according to a prior distribution f (β moderator*group ~ *f*()). Each model set, i.e., models a and b, is represented via two models: 1) a model assuming the absence of the moderator's main effect and 2) a model assuming the presence of the moderator's main effect.

We will estimate the models using the *BayesFactor* R package¹⁸ with the same prior distribution settings as in the "Continuous outcomes" section.

Hypothesis test

Each hypothesis is then evaluated by comparing all versions of the alternative hypothesis models (i.e., positive interaction between the moderator and group effect), M_{b1} (no moderator main effect) and M_{b2} (moderator main effect), to all versions of the null hypothesis models (i.e., no interaction between the moderator and group effect), M_{a1} (no moderator main effect) and M_{a2} (moderator main effect), using inclusion Bayes factors.

Bayes factor design analysis

We used standardized regression coefficients $(β)$ to define the simulation settings for continuous outcomes. We simulated data under the null hypothesis of no effect (β = 0)*,* a best guess alternative hypothesis (β = 0.30; our best guess of the possible moderation effect $-60%$ of the main effect of the group), and a pessimistic alternative hypothesis (β = 0.15; half the effect size of the best guess alternative hypothesis). For heterogeneity in effect sizes, we again follow the same logic as in the continuous outcomes, we considered no heterogeneity assuming the standard deviation of true effects is half the effect size $(\tau_{\text{moderator}}$ *treatment = 0), substantial heterogeneity $(\tau_{\text{moderator}}$ *treatment = 0.15), and extreme heterogeneity assuming the standard deviation of true effects equals the effect size $(\tau_{\text{moderator}^*treatment} = 0.30)$. For computational feasibility, we simulated only from the alternative model assuming the presence of the best guess alternative hypothesis and substantial heterogeneity in the effect. Again, we based auxiliary simulation parameters, such as the pre-treatment means, pre- and post-treatment residual variances, as well as prepost-treatment correlations on the pilot data (see Supplementary Information B).

Supplementary Fig. 4 visualizes the proportion of Bayes factors resulting in strong evidence for the alternative hypothesis under the BFDA conditions of primary interests: the null and alternative hypotheses under no and substantial heterogeneity. We verify that the specified tests provide strong evidence $BF_{10} > 10$ for the alternative hypothesis in both heterogeneity conditions under the alternative hypothesis (in all cases under no heterogeneity and in 99.7% of cases under substantial heterogeneity). Furthermore, the specified tests also provide strong evidence for the null hypothesis BF_{10} < 1/10 (in 95.6% of the no heterogeneity condition and 91.6% cases under substantial heterogeneity). See Table 4 in the Supplementary Materials on OSF for detailed performance estimates under each condition.

The robustness check under unfavorable conditions (i.e., smaller than expected effect size, excessive heterogeneity, or both), shows that the specified tests do not suffer much in the

excessive heterogeneity condition under either the null or the best guess alternative hypothesis. The largest decrease in power is under the pessimistic alternative hypothesis, yet they can provide strong evidence in approximately 55% of cases. The tests rarely find misleading evidence: In fewer than 5% of cases, we find misleading evidence in favor of the null hypothesis in all but under the pessimistic alternative hypothesis and excessive heterogeneity (13.2%), and in only 2.4% of cases we find misleading evidence in favor of the alternative hypothesis under the presence of excessive heterogeneity.

Note. The proportion of strong evidence (BF₁₀ > 10; *y*-axis) across different effect sizes of the interactions of moderator and group membership *(x*-axis) and between-country heterogeneity of the effect sizes ("No" = countries differ only in the baseline measure, "Substantial" = countries differ in both the baseline and effect sizes of the interactions of moderator and group membership). Results are based on one-sided inclusion Bayes factors from Bayesian model-averaged mixed-effects linear regressions, with no multiple comparison adjustment.

Planned exploratory analyses

Between-country heterogeneity

We will perform follow-up exploratory analyses of the between-country heterogeneity in group effects specified in the "Continuous outcomes" and "Ordinal outcomes" sections (i.e., H_{1a-e} , H_{2a-h} , and H_{3a-c}). We use the same models as specified in the aforementioned sections; however, we group the models into different sets to perform an inclusion Bayes factor test for the presence vs. absence of between-county heterogeneity (BF_f) in the group effects.

The alternative hypothesis of the presence of between-county heterogeneity in the group effects is represented via all models assuming the presence of between-county

heterogeneity ($\tau_{\text{group}} = g()$) regardless of whether the effect is present or not in continuous outcomes, or the assumed response pattern change in ordinal outcomes. The null hypothesis of the absence of the between-county heterogeneity in the group effects is represented via all models assuming the absence of the between-county heterogeneity $(\tau_{\text{group}} = 0)$ regardless of whether the effect is present or not in continuous outcomes, or the assumed response pattern change in ordinal outcomes. Please refer to the corresponding section in the Supplementary Materials on OSF for details on model parameterizations.

Supplementary Fig. 5A visualizes the proportion of Bayes factors resulting in strong evidence either for or against the presence of the between-country heterogeneity in group differences of continuous outcomes aggregated across the alternative hypotheses about the presence vs. absence of the effect. We find that the specified tests always provide strong evidence BF_{rf} > 10 for the presence of heterogeneity in both heterogeneity conditions. Furthermore, the specified tests also provide strong evidence for the absence of heterogeneity BF_{rf} < 1/10 in 60.2% of the cases when heterogeneity is absent (although they provide misleading strong evidence for the presence of heterogeneity in 12.6% of such cases). See Table 3 in the Supplementary Materials on OSF for detailed performance estimates under each condition.

Supplementary Fig. 5B visualizes the proportion of Bayes factors resulting in strong evidence either for or against the presence of the between-country heterogeneity in group differences of ordinal outcomes aggregated across the alternative hypotheses about the presence vs. absence of the effect. We find that the specified tests provide strong evidence BF_{rf} > 10 for the presence of heterogeneity in only 18.0% of cases under substantial heterogeneity and in 90.6% of cases under extreme heterogeneity condition. Furthermore, the specified tests also provide strong evidence for the absence of heterogeneity $BF_{rf} < 1/10$ in 47.8% of the cases when heterogeneity is absent. The rate of misleading evidence for either the absence or presence of heterogeneity is low (3.2% and 0.4%, respectively). See Table 6 in the Supplementary Materials on OSF for detailed performance estimates under each condition.

Supplementary Fig. 6A: Results of Bayes Factor Design Analysis for Heterogeneity in Continuous Outcomes.

 $\tau_{\text{Cohen's d}}$ *Note*. The proportion of strong evidence (BFrf > 10 or BFrf > 1/10; *y*-axis) either against or for the presence of between-country heterogeneity in group differences (blue and red lines, respectively) aggregated across the

alternative hypotheses about the presence vs. absence of the effect*.* Results are based on one-sided inclusion Bayes factors from Bayesian model-averaged mixed-effects linear regressions, with no multiple comparison adjustments.

Supplementary Fig. 6B: Results of Bayes Factor Design Analysis for Heterogeneity in Ordinal Outcomes.

Note. The proportion of strong evidence (BF_{rf} > 10 or BF_{rf} > 1/10; *y*-axis) either against or for the presence of between-country heterogeneity in group differences (blue and red lines, respectively) aggregated across the alternative hypotheses about the presence vs. absence of the effect*.* Results are based on onesided inclusion Bayes factors from Bayesian model-averaged mixed-effects cumulative probit regressions, with no multiple comparison adjustments.

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