**What We Think Others Think About Climate Change:**

**Generalizability of Pluralistic Ignorance Across 11 Countries**

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Sandra J. Geiger1\*, Jana K. Köhler1, Zenith N. C. Delabrida2, Karla A. Garduño-Realivazquez3, Christian A. P. Haugestad4, Hirotaka Imada5, Aishwarya Iyer6, Carya Maharja7, Daniel C. Mann8, Michalina Marczak9, Olivia Melville10, Sari R. R. Nijssen1, Nattavudh Powdthavee11, Radisti A. Praptiwi12, Gargi Ranade13, Claudio D. Rosa14, Valeria Vitale15, Małgorzata Winkowska16, Lei Zhang17,18,19, & Mathew P. White20

1Environmental Psychology, Department of Cognition, Emotion, and Methods in Psychology, Faculty of Psychology, University of Vienna, Wächtergasse 1, A-1010 Vienna, Austria

2Department of Psychology, Universidade Federal de Sergipe, Brazil

3Social Science Division, Universidad de Sonora, Hermosillo, Sonora, Mexico

4Department of Psychology, University of Oslo, Oslo, Norway

5School of Economics and Management, Kochi University of Technology, Kochi, Japan

6Department of Psychology, Christ (Deemed to be) University, Bangalore, India

7Yayasan Puspa Hanuman Indonesia, Bogor, Indonesia

8Konrad Lorenz Institute of Ethology, University of Veterinary Medicine, Vienna, Savoyenstraße 1, A-1160, Vienna, Austria

9Department of Psychology, NTNU - Norwegian University of Science and Technology, Trondheim, Norway

10Biology Department, University of Victoria, Victoria, Canada

11Department of Economics, Nanyang Technological University, Singapore

12Sustainability Research Cluster and Department of Biotechnology, Universitas Esa Unggul, Jakarta, Indonesia

13The Alternative Story, Bengaluru, India

14Development and Environment, Universidade Estadual de Santa Cruz, Ilhéus, Brazil

15Department of Psychology of Developmental and Socialization Processes, Faculty of Medicine and Psychology, Sapienza University of Rome, Rome, Italy

16Department of Ecology and Environmental Science, Umeå University, Umeå, Sweden

17Social, Cognitive and Affective Neuroscience Unit, Department of Cognition, Emotion, and Methods in Psychology, Faculty of Psychology, University of Vienna, Liebiggasse 5, A-1010 Vienna, Austria

18Centre for Human Brain Health, School of Psychology, University of Birmingham, Birmingham B15 2TT, United Kingdom

19Institute for Mental Health, School of Psychology, University of Birmingham, Birmingham B15 2TT, United Kingdom

20Cognitive Science Hub, University of Vienna, Liebiggasse 5, A-1010 Vienna, Austria

**Author Note**

Sandra J. Geiger https://orcid.org/0000-0002-3262-5609

Jana K. Köhler https://orcid.org/0000-0002-1581-3202

Zenith N. C. Delabrida https://orcid.org/0000-0003-1878-6040

Karla Alejandra Garduño-Realivazquez https://orcid.org/0000-0002-5199-9163

Christian A. P. Haugestad https://orcid.org/0000-0001-6787-1992

Hirotaka Imada https://orcid.org/0000-0003-3604-4155

Aishwarya Iyer  https://orcid.org/0000-0002-8277-8830

Carya Maharja https://orcid.org/0000-0001-9581-8283

Daniel C. Mann https://orcid.org/0000-0002-6260-8615

Michalina Marczak  https://orcid.org/0000-0002-2270-811X

Sari R. R. Nijssen <https://orcid.org/0000-0002-0340-8509>

Nattavudh Powdthavee  https://orcid.org/0000-0002-9345-4882

Radisti A. Praptiwi https://orcid.org/0000-0002-1657-6982

Claudio D. Rosa http://orcid.org/0000-0002-1939-2716

Valeria Vitale  https://orcid.org/0000-0003-1073-3390

Lei Zhang https://orcid.org/0000-0002-9586-595X

Mathew P. White https://orcid.org/0000-0002-4168-7289

This work had been preregistered on PsychArchives (<http://dx.doi.org/10.23668/psycharchives.7059>; June 29, 2022). Data collection was funded by the Leibniz Institute for Psychology (ZPID). We thank Lu-Ning He, Caroline Marrs, Nateecha Powdthavee, Viviana Vitale, and Alice Yamamoto-Wilson for their help with the back-translation. We thank Univ.-Prof. Mag. Mag. Dr. Dr. Dr. Martin Voracek for feedback on earlier versions of this manuscript and the analysis strategy. All datasets and analysis code mentioned in this article will be shared upon article publication.

\*Correspondence concerning this article may be addressed to Sandra J. Geiger, Environmental Psychology, Department of Cognition, Emotion, and Methods in Psychology, Faculty of Psychology, University of Vienna, Wächtergasse 1, A-1010 Vienna, Austria. Phone: +43-1-4277-47154, E-mail: [sandra.geiger@univie.ac.at](mailto:sandra.geiger@univie.ac.at).

# Abstract

The majority of people worldwide believe in human-caused climate change. Yet this social consensus is often underestimated, potentially undermining individual climate action. This preregistered study tests (a) whether systematic misperceptions of climate change beliefs generalize across a diverse sample of 11 countries, particularly those countries that are typically underrepresented in psychological research, and (b) whether presenting country-specific public opinion data on climate change beliefs can promote factors related to climate action. Using cross-quota samples (age and sex; *N* = 3,653), we find that people across all 11 countries underestimate the prevalence of pro-climate views (‘mainly and partly human-caused’), ranging from ‑7.5% in Indonesia to ‑20.8% in Brazil. However, providing social consensus information is largely ineffective, except for minimal effects on willingness to express one’s opinion on climate change. This effect may, nevertheless, be meaningful if it reduces ‘self-silencing’. The overall results question the continued use of social consensus messaging on social media and as an educational intervention.

*Keywords:* climate change, pluralistic ignorance, social consensus, second-order beliefs, social norms, misperceptions, cross-country generalizability

**What We Think Others Think About Climate Change:**

**Generalizability of Pluralistic Ignorance Across 11 Countries**

The vast majority of people worldwide believe in human-caused climate change1, yet this social consensus is often systematically misperceived. Several studies find that people substantially underestimate the prevalence of pro-climate views and overestimate the prevalence of skeptical views in their country2–6. This phenomenon is known as pluralistic ignorance7 and refers to many group members systematically misperceiving what most others think8, either in absolute (i.e., misperceiving minority as majority opinions) or relative terms (i.e., overestimating minority opinions but not to the point of misperceiving the minority as a majority)4,9–11. Pluralistic ignorance, such as underestimating the prevalence of pro-climate views, can have far-reaching societal consequences: It may discourage people from talking about climate change12, hamper support for climate policies5, and undermine climate action2,13.

Arguably, the most nuanced assessment of pluralistic ignorance regarding climate change beliefs comes from a 2013 study by Leviston and colleagues4. Indicative of absolute pluralistic ignorance, Australians underestimated how many of their fellow citizens believed in human-caused climate change (perceived: 33.7% vs. actual: 50.4% in 2010). They also underestimated the number of attribution skeptics14, namely those who believed in natural-caused climate change (perceived: 23.7% vs. actual: 40.2% in 2010). In turn, they, on average, overestimated the number of trend skeptics14, or those who did not believe in climate change (perceived: 21.6% vs. actual: 5.6% in 2010), and those who did not know whether the climate was changing (perceived: 20.9% vs. actual: 3.8% in 2010).

The accuracy of these estimates varied depending on individual climate change beliefs4. Climate change believers and attribution skeptics underestimated their back then widely held own opinion the least, whereas trend skeptics overestimated their minority opinion the most compared to all other groups4. These findings are consistent with false consensus effects15,16, which may arise because individuals tend to surround themselves with like-minded people4,15. Skeptics are more likely to be exposed to views that are similar to theirs, potentially exacerbating their overestimation. At the same time, climate change believers are more likely to be exposed to pro-climate views, weakening the extent to which they underestimate the prevalence of their own beliefs.

The study by Leviston and colleagues4 may have yielded exceptionally high pluralistic ignorance effects because climate change is a polarized and politicized issue, as well as a frequent source of public conflict in Australia17,18. While several US studies2,3,5,6 report similar levels of misperceptions, public opinion on climate change is equally polarized and politicized in the US19. Besides polarization, both countries are high in cultural looseness, meaning they are characterized by more ambiguous norms and more tolerance for norm violations20, which may contribute to exceptionally high pluralistic ignorance effects21. One of the aims of the present study is to conceptually replicate Leviston et al.’s work and test whether pluralistic ignorance regarding climate change beliefs generalizes across a diverse set of 11 countries (Brazil, Canada, China, Germany, India, Indonesia, Italy, Japan, Mexico, Poland, and Thailand; *Aim 1*), including several countries that are less polarized, culturally tighter (i.e., clearer social norms with stricter sanctions for norm deviations20), and typically underrepresented in psychological research (see Methods for the full rationale on the country selection).

Underestimating the prevalence of pro-climate views can have far-reaching adverse consequences: It may cause self-silencing among those who hold pro-climate views12, which may exacerbate the impression that pro-climate views are not widely shared and thus further discourage societal discourse around climate change (the so-called ‘spiral of silence’22). Both correlational3 and experimental5 evidence suggest that underestimating pro-climate views can hamper support for climate policies. It can further pressure people to conform to misperceived views of others23 and, in turn, potentially discourage climate action13.

On the bright side, these systematic misperceptions provide an opportunity for simple and scalable interventions24 that involve disclosing the actual social consensus on climate change—the fact that most members of society believe climate change is happening and human-caused25—to ultimately promote factors related to climate action. Although this intervention is used in social media posts26 and online educational quizzes (e.g., ‘Worldview Upgrader’: UN Goal 13 Climate Action27), its effectiveness has rarely been investigated empirically. A recent meta-analysis28 shows that more than half of the social consensus interventions shift perceptions about others by at least 25%; however, only one of these interventions is related to climate change specifically5.

In addition to shifting targeted beliefs (e.g., about others’ climate change beliefs), social consensus interventions may influence non-targeted perceptions (e.g., of others’ climate action or policy support), behavioral intentions, and behaviors, especially directly after the intervention28. Several studies show that country-level norms, as used in the current intervention, are effective. For example, Mildenberger and Tingley5 find that informing Americans about actual climate change beliefs of Chinese people increases non-targeted beliefs, namely Americans’ expectations of Chinese compliance to a US-Chinese climate agreement. That belief shift boosts support for such an agreement. Similarly, a country-wide norm message about how many Americans try to fight climate change can increase Americans’ willingness to fight climate change compared to a control condition29, and emphasizing how many Americans are angry about climate inaction can improve Americans’ personal climate change beliefs and policy support30. More generally, informing people that a majority holds pro-climate views, supports climate policies, or engages in pro-environmental actions can reduce misperceptions and subsequently increase willingness to discuss12 and fight29 climate change, pro-environmental behavior such as energy saving31,32, and support and prioritization of climate policies5,29,31,33–35. Moreover, initial descriptive evidence shows that Americans are more willing to support certain climate policies and to join a campaign on climate change when they perceive that a majority (vs. a minority) of Americans think that climate change is happening2.

However, such norm interventions are not a one-size-fits-all approach. Social identity theory36 suggests that interventions are most effective for those who strongly identify with the group referenced in the intervention. For example, descriptive norm messages increase intentions to eat more vegetables, but only among those who strongly identify with the referent group37,38 (e.g., university or nation; see recent review39 for an overview of social norms regarding climate change). Based on a misperception correction perspective, previous work suggests that various consensus messages are more effective among those who underestimate the consensus more40,41. Similarly, the effectiveness of the current intervention may be moderated by (a) individuals’ sense of identity with the referent group and (b) their prior social consensus perceptions.

Going beyond testing the generalizability of Leviston et al.’s work (*Aim 1*), we also investigate whether and for whom a simple social consensus intervention, namely presenting country-specific public opinion data on actual climate change beliefs based on YouGov data1, can promote factors related to climate action (*Aim 2*). To achieve both aims, we conducted an online survey experiment among cross-quota samples based on age and sex (*N* = 3,653). While the original study used four categories to assess climate change beliefs (mainly human-caused, not human-caused, not happening, and don’t know), we add a fifth category (partly human-caused) to (a) capture widely held beliefs that climate change is caused by both natural processes and human activity (27-64% depending on the country1) and (b) test a social consensus intervention—which uses pre-existing, real-world data on the actual distribution of climate change beliefs in each of the studied countries (see Supplement A for a comparison between the original and the present study).

In terms of pluralistic ignorance, we expect that individuals would underestimate the number of climate change believers in their country, overestimate the number of attribution and trend skeptics and that these over- and underestimation effects would be moderated by individuals’ own opinions (Table 1). Of note, while participants in the original study underestimated the percentage of attribution skeptics, we expect that this number would be overestimated because descriptive evidence shows that attribution skeptics are a minority of 5% (Brazil, China, and Japan) to 18% (Indonesia) in all countries of interest1. This updated hypothesis is consistent with the phenomena of pluralistic ignorance and findings from later US studies on misperceptions of climate change beliefs5.

Regarding the intervention’s effectiveness, we expect that informing climate change believers about the real-world social consensus on climate change in their country would lead to (a) a higher willingness to express their opinion on climate change, (b) a higher willingness to change their own lifestyle and support government action, (c) higher expectations about fellow citizens’ willingness to change their lifestyle and support for government action on climate change, and (d) higher beliefs about citizens’ efficacy to contribute to reducing climate change (Table 1). We also explore whether the intervention is especially effective for climate change believers with high national identification and those who previously underestimated the social consensus in their country (not preregistered).

**Table 1**

***Overview of the Preregistered Hypotheses and Research Questions***

|  |  |
| --- | --- |
| **Aim** | **Description of Hypothesis/Research Question** |
| Pluralistic ignorance effects | **H1:** Individuals underestimate the number of people in their country who believe that climate change is (a) mainly and (b) partly human-caused. |
| Individuals overestimate the number of (c) attribution and (d) trend skeptics in their country. |
| **H2:** Individuals who believe that climate change is (a) mainly and (b) partly human-caused underestimate the prevalence of this opinion in their country the least compared to other belief groups. |
| (c) Attribution and (d) trend skeptics overestimate the prevalence of this opinion the most compared to other belief groups. |
| Generalizability | **RQ1:** Do the pluralistic ignorance effects (H1a-d) generalize across countries? |
| Effectiveness of the intervention | Climate change believersa in the intervention (vs. control) condition:  **H3:** are more willing to express their opinion on climate change. |
| **H4a:** are more willing to make changes to their lifestyle to mitigate climate change. |
| **H4b:** expect more fellow citizens to be willing to make at least some changes to their lifestyle to mitigate climate change. |
| **H5a:** are more likely to view government action on climate change as a higher priority. |
| **H5b:** are more likely to expect that their fellow citizens view government action on climate change as a high or very high priority. |
| **RQ2:** Do climate change believers in the intervention (vs. control) condition believe more strongly that their country’s citizens can contribute to reducing climate change (i.e., group efficacy beliefs)? |
| Effectiveness of the intervention for different audiences | **H6:** The effects of the intervention on (a) willingness to make lifestyle changes to mitigate climate change and (b) support for government action on climate change are stronger for climate change believers with higher rather than lower national identification.  **RQ3:** Is the effect of the intervention on group efficacy beliefs stronger for climate change believers with higher rather than lower national identification?  **Exploratory (not pre-registered):** Is the intervention effective among those who underestimated the social consensus prior to the intervention? |

Note. aWe focus on climate change believers because some of the expected effects may differ for climate change skeptics. For example, willingness to discuss may be higher for climate change believers after the intervention as they learn their opinion is the majority opinion. In contrast, it may be lower for climate change skeptics as they learn their opinion is the minority opinion12. However, prior to data collection, we expected few climate change skeptics in our samples and, thus, insufficient statistical power to test whether individual climate change beliefs moderate the intervention’s effectiveness.

# Results

## Overview

The data analyses focus on two broad questions: first, to what extent people from 11 countries misperceive the social consensus on climate change in their country, and second, whether providing country-specific information on the actual public opinion on climate change is effective at promoting factors related to climate action among climate change believers.

## Pluralistic Ignorance Across Countries

To formally test to what extent people misperceive the social consensus on climate change, we estimate Bayesian zero-one-inflated random-effects models with participants (level 1) nested in countries (level 2). For these analyses, we reweight the existing cross-quota samples (age and sex) based on the distribution of climate change beliefs in the YouGov survey to ensure adequate representation of all belief groups (for details, see Methods). For all models, diagnostics were good: the chains converged, the effective sample sizes were large, all were close to 1.0, there were no divergent transitions, and posterior predictive checks showed that the models adequately describe the data.

Regarding pluralistic ignorance (*N* = 3,653; *n* = 328-354 per country), we find reliable differences in the expected direction between the actual beliefs derived from the YouGov data and the perceived beliefs in our sample. As shown in Figure 1, pro-climate views, ‘mainly human-caused’ (dark blue dots) and ‘partly human-caused’ (light blue dots), are relatively consistently underestimated compared to the YouGov data (dark and light blue crosses). In contrast, skeptical views, ‘not human-caused’ (light red) and ‘not happening’ (dark red), are consistently overestimated across all studied countries.

**Figure 1**

*Actual and Perceived Prevalence (in %) of Different Climate Change Beliefs by Country*

*Note.* Colors indicate the four climate change beliefs (i.e., mainly human-caused, partly human-caused, not human-caused, and not happening). The fifth category, ‘don’t know,’ is not displayed. The crosses indicate the actual percentage of participants who endorsed each of the beliefs in the YouGov survey1; the error bars indicate the margins of error based on 95% confidence intervals, calculated using the R package *moe* (Version 0.9.1)42. The dots indicate posterior means of participants’ estimates of what percentage of people in their country endorse each of the four climate change beliefs. These posterior means are based on Bayesian multi-level zero-one inflated regression models. The error bars indicate 95% equal-tailed credible intervals, calculated using the R package *bayestestR* (Version 0.13.1)43. Countries are ordered alphabetically. Sample sizes range from 328 in Italy and Mexico to 354 in Japan (total *n* = 3,653). Across countries, people relatively consistently underestimate pro-climate views (dark and light blue) and consistently overestimate skeptical views (dark and light red).

Consistent with Hypothesis 1a, we find at least moderate evidence that people in seven out of 11 countries underestimate the number of those who believe in mainly human-caused climate change, ranging from minor underestimation of -1.2% (90% CrI [-3.5%, 1.2%]; BF-+ = 3.78) in Canada to more substantial underestimation of -12.2% (90% CrI [‑15.1%, -9.3%]; BF-+ → ∞) in Brazil (Table 2). However, we also find extremely strong evidence that people in the remaining four countries overestimate the size of this group, ranging from 3.8% (90% CrI [1.5%, 6.2%]; BF+- = 311.53) of overestimation in Indonesia to 17.3% (90% CrI [15.2%, 19.5%]; BF+- → ∞) in China (Table 2). Remarkably, these four countries—China, Germany, Japan, and Indonesia—have the lowest prevalence of ‘mainly human-caused’ beliefs (23-36% vs. 39-55% in the other seven countries1). These findings align with the phenomenon of pluralistic ignorance, as smaller proportions increase the chances of over- rather than underestimation. To summarize, we find mixed evidence for Hypothesis 1a in terms of presence and magnitude of the effect.

In line with Hypothesis 1b, there is extreme support that people across all 11 countries underestimate the number of those who believe in partly human-caused climate (Table 2). All credible intervals indicate that these underestimation effects are extremely unlikely to be zero, and the corresponding Bayes factors suggest that the data are much more likely under the hypothesis that people underestimate (H-) rather than overestimate (H+) the size of the ‘partly human-caused’ group. However, the underestimation effects vary in terms of magnitude from ‑29.1% (90% CrI [‑31.0%, ‑27.2%]; BF-+ → ∞) in China to ‑2.9% (90% CrI [-4.7%, ‑1.0%]; BF-+ = 203.78) in India. This is again in line with the phenomenon of pluralistic ignorance: Based on the YouGov data1, 27% of Indians believe that climate change is partly human-caused, whereas 64% of Chinese nationals hold this belief. Such larger majorities, as in China, leave more room for stronger underestimation effects. Overall, we find extremely strong evidence in all countries that people underestimate the number of those who believe in partly human-caused climate change, with varying magnitudes across countries.

Supporting Hypothesis 1c, we find extremely strong evidence that people overestimate the number of attribution skeptics—those that do not believe in the human causation of climate change—in all countries except Indonesia and Mexico. This overestimation ranges from 2.9% (90% CrI [1.4%, 4.4%]; BF+- = 3,749.00) in India to 7.4% (90% CrI [6.0%, 8.8%]; BF+- → ∞) in Germany (Table 2). Based on the YouGov data1, attribution skeptics are a minority in all countries; however, in our sample, the group of attribution skeptics is largest in Indonesia (18%) and Mexico (14%) compared to the remaining countries (5-11%)—which might explain the exceptional pattern in these two countries. Consistent with Hypothesis 1d, we also find extremely strong evidence across all 11 countries that people overestimate the number of trend skeptics—those that do not believe in climate change. This overestimation ranges from 6.2% (90% CrI [5.1%, 7.3%]; BF+- → ∞) in China to 11.1% (90% CrI [9.7%, 12.5%]; BF+- → ∞) in Mexico (Table 2). Overall, we find largely consistent and extremely strong evidence across the studied countries that people underestimate the number of both attribution and trend skeptics in their countries.

In addition, we test whether the results hold when taking sampling uncertainty regarding the actual percentages of climate change beliefs into account. Specifically, we test whether the perceived percentages in our samples are equal to a range of actual percentages. To do so, we define a region of practical equivalence (ROPE)43,44—a range of actual percentages defined as the actual percentages of climate change beliefs from the YouGov survey ± the margins of error based on 95% confidence intervals (see Methods for details). If only a small proportion of the 95% credible interval of the posterior distribution falls within the ROPE, then the perceived percentages are not practically equivalent to the actual percentages. As shown in Table 2, all results concerning Hypotheses 1a-d hold when considering this sampling uncertainty.

To ensure comparability with previous research5, we collapse the belief groups into two categories, namely believers (‘mainly human-caused’ and ‘partly human-caused’) and non-believers (‘not human-caused’, ‘not happening’, and ‘don’t know’). We find extremely strong support that people across all countries underestimate the number of climate change believers or, in other words, overestimate the number of non-believers. The findings correspond to substantial relative pluralistic ignorance effects that are extremely unlikely to be zero (Table 2). While people in every studied country substantially underestimate the number of believers, from ‑20.8% (90% CrI [-23.4%, -18.2%]; BF-+ → ∞) in Brazil to -7.5% (90% CrI [-10.1%, -5.1%]; BF-+ → ∞) in Indonesia (Figure ), they consistently perceive the group of believers as an absolute majority (> 50%).

Table 2

*Summary of the Pluralistic Ignorance Effects across all Country*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Country** | **Mean pluralistic ignorance [90% CrI]** | **Bayes factor** | **Evidence in favor of / against Hypothesis** | **% inside region of practical equivalence**  **(ROPE)** |
| ***H1a:*** *‘mainly human-caused’* | | | | |
| Brazil | -12.2% [‑15.1, ‑9.3] | BF-+ → ∞ | Extreme  **●●●●●** | 0.0% |
| Canada | -1.2%  [-3.5, 1.2] | BF-+ = 3.78 | Moderate  **●●**○○○ | 92.2% |
| China | 17.3%  [15.2, 19.5] | BF+- → ∞ | Extreme  ●●●●● | 0.0% |
| Germany | 5.4% [3.2%, 7.6%] | BF+- → ∞ | Extreme  ●●●●● | 0.0% |
| India | -8.5%  [-11.2, -5.8] | BF-+ → ∞ | Extreme  ●●●●● | 0.0% |
| Indonesia | 3.8% [1.5, 6.2] | BF+- = 311.53 | Extreme  ●●●●● | 20.7% |
| Italy | -2.7%  [-5.1, -0.2] | BF-+ = 24.09 | Strong  ●●●○○ | 49.9% |
| Japan | 5.7%  [3.3, 8.1] | BF+- → ∞ | Extreme  ●●●●● | 0.7% |
| Mexico | -8.5%  [-11.1, -5.9] | BF-+ → ∞ | Extreme  ●●●●● | 0.0% |
| Poland | -5.5%  [-7.9, -3.1] | BF-+ =14,999.00 | Extreme  ●●●●● | 2.0% |
| Thailand | -6.0%  [-8.3, -3.8] | BF-+ = 59,999.00 | Extreme  ●●●●● | 0.0% |
|  |  |  |  |  |
| ***H1b:*** *‘partly human-caused’* | | | | |
| Brazil | -7.6%  [-9.5, -5.7] | BF-+ → ∞ | Extreme  ●●●●● | 0.0% |
| Canada | -14.1%  [-15.8, -12.3] | BF-+ → ∞ | Extreme  ●●●●● | 0.0% |
| China | -29.1% [-31.0, -27.2] | BF-+ → ∞ | Extreme  ●●●●● | 0.0% |
| Germany | -21.7% [-23.3, -20.0] | BF-+ → ∞ | Extreme  ●●●●● | 0.0% |
| India | -2.9% [-4.7, -1.0] | BF-+ = 203.78 | Extreme  ●●●●● | 42.7% |
| Indonesia | -10.3% [-12.1, 8.4] | BF-+ → ∞ | Extreme  ●●●●● | 0.0% |
| Italy | -10.6%  [-12.3, 8.9] | BF-+ → ∞ | Extreme  ●●●●● | 0.0% |
| Japan | -18.9%  [-20.7, -17.0] | BF-+ → ∞ | Extreme  ●●●●● | 0.0% |
| Mexico | -7.6%  [-9.3, -5.8] | BF-+ → ∞ | Extreme  ●●●●● | 0.0% |

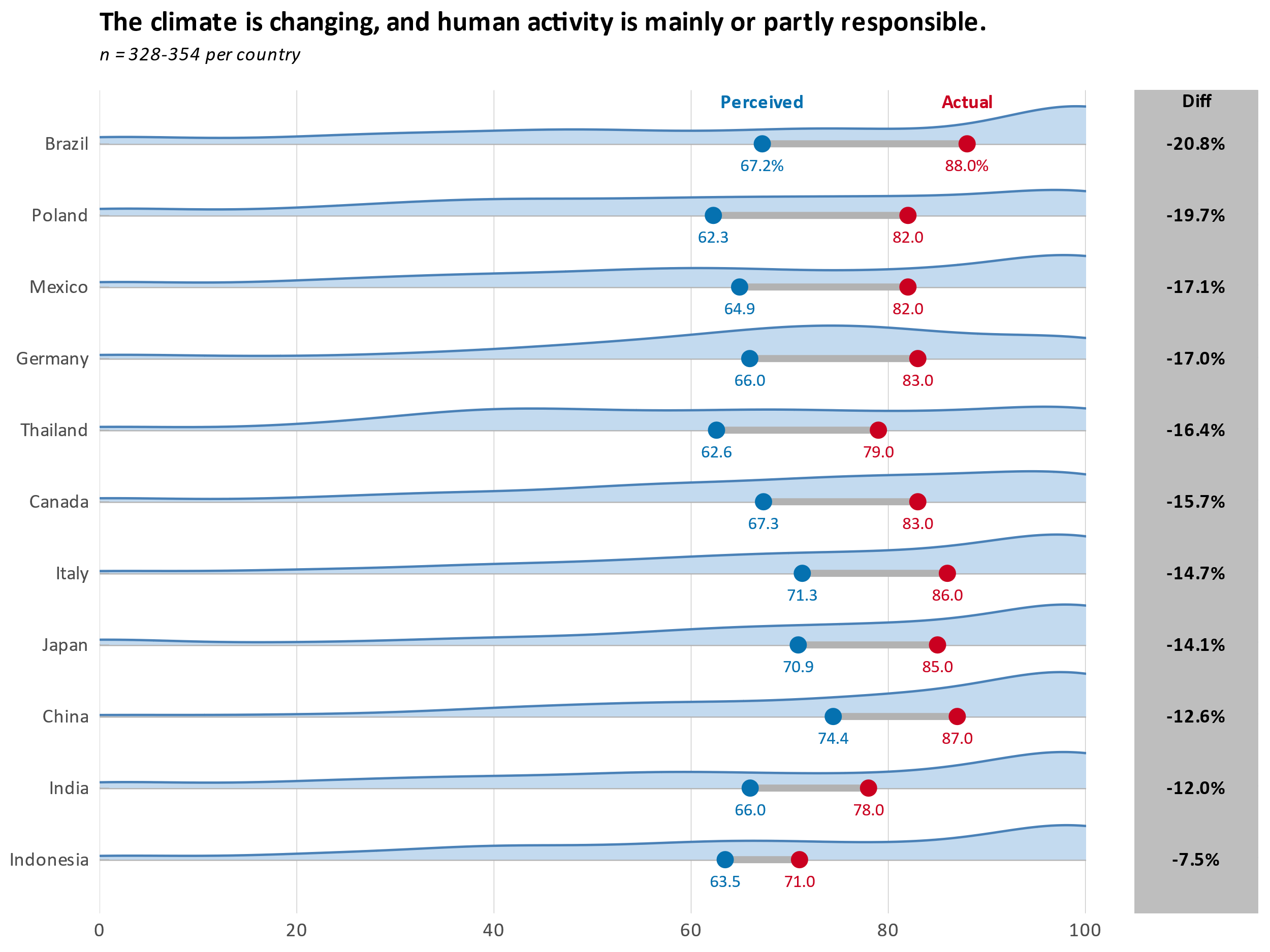
|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Poland | -12.7%  [-14.4, -11.0] | BF-+ → ∞ | Extreme  ●●●●● | 0.0% |
| Thailand | -8.7%  [-10.2, -7.0] | BF-+ → ∞ | Extreme  ●●●●● | 0.0% |
|  |  |  |  |  |
| ***H1c:*** *‘not human-caused’* | | | | |
| Brazil | 7.3%  [6.1, 8.6] | BF+- → ∞ | Extreme  ●●●●● | 0.0% |
| Canada | 4.8%  [3.7, 6.1] | BF+- → ∞ | Extreme  ●●●●● | 0.0% |
| China | 7.2%  [6.0, 8.4] | BF+- → ∞ | Extreme  ●●●●● | 0.0% |
| Germany | 7.4%  [6.0, 8.8] | BF+- → ∞ | Extreme  ●●●●● | 0.0% |
| India | 2.9%  [1.4, 4.4] | BF+- = 3,749.00 | Extreme  ●●●●● | 11.3% |
| Indonesia | -3.4%  [-4.7, -2.0] | BF-+ → ∞ | Extreme  ●●●●● | 6.9% |
| Italy | 6.5%  [5.3, 7.7] | BF+- → ∞ | Extreme  ●●●●● | 0.0% |
| Japan | 4.9%  [3.7, 6.2] | BF+- → ∞ | Extreme  ●●●●● | 0.0% |
| Mexico | 0.1%  [-1.2, 1.4] | BF+- = 1.09 | Weak  ●○○○○ | 100.0% |
| Poland | 6.3%  [5.2, 7.6] | BF+- → ∞ | Extreme  ●●●●● | 0.0% |
| Thailand | 6.0%  [4.7, 7.4] | BF+- → ∞ | Extreme  ●●●●● | 0.0% |
|  |  |  |  |  |
| ***H1d:*** *‘not happening’* | | | | |
| Brazil | 8.0%  [6.6, 9.5] | BF+- → ∞ | Extreme  ●●●●● | 0.0% |
| Canada | 9.4%  [8.1, 10.9] | BF+- → ∞ | Extreme  ●●●●● | 0.0% |
| China | 6.2%  [5.1, 7.3] | BF+- → ∞ | Extreme  ●●●●● | 0.0% |
| Germany | 9.2%  [8.0, 10.4] | BF+- → ∞ | Extreme  ●●●●● | 0.0% |
| India | 7.7%  [6.2, 9.1] | BF+- → ∞ | Extreme  ●●●●● | 0.0% |
| Indonesia | 9.4%  [8.1, 10.8] | BF+- → ∞ | Extreme  ●●●●● | 0.0% |
| Italy | 8.5%  [7.3, 9.9] | BF+- → ∞ | Extreme  ●●●●● | 0.0% |
| Japan | 6.0%  [4.8, 7.5] | BF+- → ∞ | Extreme  ●●●●● | 0.0% |
| Mexico | 11.1%  [9.7, 12.5] | BF+- → ∞ | Extreme  ●●●●● | 0.0% |
| Poland | 9.8%  [8.3, 11.2] | BF+- → ∞ | Extreme  ●●●●● | 0.0% |
| Thailand | 6.8%  [5.6, 8.1] | BF+- → ∞ | Extreme  ●●●●● | 0.0% |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| ***Combined:*** *‘mainly and partly human-caused’* | | | | |
| Brazil | -20.8%  [-23.4, -18.2] | BF-+ → ∞ | Extreme  ●●●●● | 0.0% |
| Canada | -15.7%  [-18.1, -13.4] | BF-+ → ∞ | Extreme  ●●●●● | 0.0% |
| China | -12.6%  [-15.0, -10.2] | BF-+ → ∞ | Extreme  ●●●●● | 0.0% |
| Germany | -17.0%  [-19.4, -14.8] | BF-+ → ∞ | Extreme  ●●●●● | 0.0% |
| India | -12.0%  [-14.6, -9.5] | BF-+ → ∞ | Extreme  ●●●●● | 0.0% |
| Indonesia | -7.5%  [-10.1, -5.1] | BF-+ → ∞ | Extreme  ●●●●● | 0.0% |
| Italy | -14.7%  [-17.1, -12.4] | BF-+ → ∞ | Extreme  ●●●●● | 0.0% |
| Japan | -14.1%  [-16.5, -11.8] | BF-+ → ∞ | Extreme  ●●●●● | 0.0% |
| Mexico | -17.1%  [-19.6, -14.6] | BF-+ → ∞ | Extreme  ●●●●● | 0.0% |
| Poland | -19.7%  [-22.3, -17.3] | BF-+ → ∞ | Extreme  ●●●●● | 0.0% |
| Thailand | -16.4%  [-18.7, -14.2] | BF-+ → ∞ | Extreme  ●●●●● | 0.0% |

*Note.* The mean represents the posterior difference between the actual percentage of beliefs in the YouGov survey and the perceived percentages in this sample. Positive values indicate overestimation; negative values indicate underestimation. CrI = credible interval. BF-+ indicates one-sided testing of two competing hypotheses—that the actual percentage is underestimated (H-) vs. that the actual percentage is overestimated (H+). BF-+= 10 would, therefore, mean that the data are ten times more likely under the H-of underestimation than the H+ of overestimation, whereas BF+- = 10 would indicate the opposite. The column ‘evidence’ categorizes the strength of evidence according to Jeffreys45 (Supplement B): Insufficient evidence: ○○○○○; weak evidence: ●○○○○; moderate evidence: ●●○○○; strong evidence: ●●●○○; very strong evidence: ●●●●○; extremely strong evidence:●●●●●. Blue indicates evidence in favor of the tested hypothesis; red indicates evidence against it. The column ‘% inside region of practical equivalence (ROPE)’ indicates the proportion of the 95% equal-tailed credible interval of the posterior distribution that falls within the ROPE, defined as the percentage of each belief category from the YouGov survey ± the margins of error based on the 95% confidence interval to account for sampling uncertainty.

**Figure 2**

*Actual (Red) and Perceived (Blue) Prevalence (in %) of Pro-Climate Beliefs (‘Mainly Human-Caused’ and ‘Partly Human-Caused’) by Country*

**

*Note.* The blue area represents the distribution of perceived percentages of climate change believers per country. The blue dot represents the posterior mean of the perceived percentage of climate change believers per country, based on multi-level zero-one inflated regression models. The red dot represents the actual percentage of climate change believers based on the YouGov data. The Diff column represents the difference between the perceived and actual percentages per country. Negative values indicate that people, on average, underestimate the percentage of climate change believers in their country. Countries are ordered by the magnitude of pluralistic ignorance, from largest to smallest.

For Hypotheses 2a-d, we planned to test whether perceptions of others’ climate change beliefs depend on one’s own beliefs. We refrain from testing these hypotheses due to the low number of skeptics (weighted *n* = 427; 11.7%) across countries and especially within each country (China: weighted *n* = 15 or 11.9% to Indonesia: weighted *n* = 66 or 20.1%).

## Intervention Effects

The intervention targeted climate change believers and informed them about the actual distribution of climate change beliefs in their country based on recent YouGov data1 (Table 3). We find extremely strong support in all countries but Indonesia that climate change believers underestimate rather than overestimate the size of their group compared to the YouGov data—a prerequisite for the intervention to be effective. This effect ranges from an underestimation of -14.5% (90% CrI [-16.8%, -12.2%]; BF-+ → ∞) in Brazil to a slight overestimation of 2.0% (90% CrI [-0.2%, 4.1%]; BF+- = 14.63) in Indonesia (Table 3).

Table 3

*Summary of the Pluralistic Ignorance Effects among Climate Change Believers across all Country*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Country** | **Mean pluralistic ignorance [90% CrI]** | **Bayes factor** | **Evidence in favor of / against Hypothesis** | **% inside region of practical equivalence**  **(ROPE)** |
| ***Combined:*** *‘mainly and partly human-caused’ among believers* | | | | |
| Brazil | -14.5%  [-16.8, -12.2] | BF-+ → ∞ | Extreme  ●●●●● | 0.0% |
| Canada | -10.1%  [-12.0, -8.2] | BF-+ → ∞ | Extreme  ●●●●● | 0.0% |
| China | -9.2%  [-11.2, -7.1] | BF-+ → ∞ | Extreme  ●●●●● | 0.0% |
| Germany | -12.0%  [-13.9, -10.1] | BF-+ → ∞ | Extreme  ●●●●● | 0.0% |
| India | -4.9%  [-7.1, -2.7] | BF-+ = 19,999.00 | Extreme  ●●●●● | 1.2% |
| Indonesia | 2.0%  [-0.02, 4.1] | BF+- = 14.63 | Strong  ●●●○○ | 72.3% |
| Italy | -9.8%  [-11.7, -7.8] | BF-+ → ∞ | Extreme  ●●●●● | 0.0% |
| Japan | -8.1%  [-10.1, -6.1] | BF-+ → ∞ | Extreme  ●●●●● | 0.0% |
| Mexico | -10.8%  [-13.0, -8.6] | BF-+ → ∞ | Extreme  ●●●●● | 0.0% |
| Poland | -13.4%  [-15.7, -11.2] | BF-+ → ∞ | Extreme  ●●●●● | 0.0% |
| Thailand | -10.0%  [-12.2, -7.9] | BF-+ → ∞ | Extreme  ●●●●● | 0.0% |

*Note.* The mean represents the posterior difference between the actual percentage of pro-climate beliefs in the YouGov survey and the perceived percentages of pro-climate beliefs among climate change believers in this sample. Positive values indicate overestimation; negative values indicate underestimation. CrI = credible interval. BF-+ indicates one-sided testing of two competing hypotheses—that the actual percentage is underestimated (H-) vs. that the actual percentage is overestimated (H+). BF-+= 10 would, therefore, mean that the data are ten times more likely under the H-of underestimation than the H+ of overestimation, whereas BF+- = 10 would indicate the opposite. The column ‘evidence’ categorizes the strength of evidence according to Jeffreys45 (Supplement B): Insufficient evidence: ○○○○○; weak evidence: ●○○○○; moderate evidence: ●●○○○; strong evidence: ●●●○○; very strong evidence: ●●●●○; extremely strong evidence:●●●●●. Blue indicates evidence in favor of the tested hypothesis; red indicates evidence against it. The column ‘% inside region of practical equivalence (ROPE)’ indicates the proportion of the 95% equal-tailed credible interval of the posterior distribution that falls within the ROPE, defined as the percentage of climate change believers from the YouGov survey ± the margins of error based on the 95% confidence interval to account for sampling uncertainty.

Concerning the intervention’s effectiveness, we observe small descriptive differences in individuals’ willingness to express their opinion on climate change between the control (*n* = 1,675) and intervention (*n* = 1,686) condition, as shown in Figure 3. For all other outcomes, we observe no noticeable differences between conditions.

Figure 3

*Comparison of the Control and Intervention Condition on the six Outcomes*



*Note.* The gray line represents the median.

We further test whether informing climate change believers about the actual distribution of climate change beliefs in their country can increase: (a) willingness to express their opinion on climate change, (b) own and others’ willingness to make changes to their lifestyle to mitigate climate change, (c) own and others’ prioritization of government action on climate change (a-c: *n* = 3,361), and (d) group efficacy beliefs (*n* = 3,186). To formally test the intervention’s effectiveness, we conducted several Bayesian multi-level regression analyses with participants (level 1) nested in countries (level 2; see Methods for details).

Including relevant control variables (see Data Analysis) and based on Jeffrey’s classification scheme for Bayes factors (Supplement B), we find moderate support for Hypothesis 3 that climate change believers are more willing to express their opinion on climate change after being exposed to the intervention compared to the control message (*b* = 0.05, *SE* = 0.04, 90% CrI [-0.02, 0.11], BF+-= 6.15). This means that climate change believers who are informed about their country’s actual climate change beliefs are 0.05 SD more willing to express their opinion on the topic than those exposed to the control message. However, based on the credible interval, the data cannot rule out a slightly negative or a null effect.

We find extremely strong evidence that the intervention does not change personal willingness to change one’s lifestyle compared to the control message (BF01 = 218.35; Hypothesis 4a). If the effect was present, it would likely be close to zero (*b* = -0.01, *SE*= 0.05, 95% CrI [-0.10, 0.08]). Similarly, expectations about others’ willingness to make lifestyle changes are not significantly higher in the intervention compared to the control condition (Hypothesis 4b; *b* = 1.49%, *t*(3,360) = 1.77, *p* = .077).

We find extremely strong evidence that the intervention does not shift personal support for government action (BF01 = 232.28; Hypothesis 5a). If the effect was present, it would likely be negligible (*b*= -0.01, *SE* = 0.04, 95% CrI [-0.09, 0.08]). Similarly, expectations about others’ government support are not significantly higher in the intervention compared to the control condition (Hypothesis 5b; *b* = 1.39%, *t*(3,360) = 1.69, *p* = .092).

Regarding group efficacy beliefs, we find extremely strong evidence against any effect on climate change believers’ beliefs about whether their country’s citizens can jointly prevent the negative consequences of climate change (BF01 = 218.81, *b* = -0.02, *SE* = 0.04, 95% CrI [‑0.10, 0.07]).

We planned to test whether the intervention is more effective for people with higher rather than lower national identification (Hypotheses 6a and b, Research Question 3). Since national identification in our sample is very high (Table 4), with only 3.51% of participants scoring below 5 (on a 0 to 10 scale), we refrained from testing the proposed hypotheses. Even with such high levels of national identification—which should theoretically provide an ideal basis for the social consensus message to be effective—the intervention is largely ineffective.

## Sensitivity and Exploratory Analyses

As a robustness check, we re-ran all analyses without control variables. These sensitivity analyses show similar results as the primary analyses, suggesting that the results are robust (Supplement C). We also conducted exploratory subgroup analyses to investigate the intervention’s effectiveness among the main target group, climate change believers who underestimated the social consensus in their country prior to being exposed to the intervention (*n* = 2,131-2,246). Consistent with the main findings, the intervention is largely ineffective even among this group (Supplement C).

# Discussion

This study investigates whether and to what extent people from a diverse set of 11 countries across the globe underestimate the prevalence of pro-climate views and overestimate the prevalence of skeptical views in their country—an example of pluralistic ignorance7–9. It further tests whether providing information about actual public opinion on climate change, based on real-world data from each country, can promote factors related to climate action.

We find broad generalizability for pluralistic ignorance in the context of climate change beliefs. Across all 11 countries, when asked about their view on fellow citizens’ climate change beliefs, people underestimate the prevalence of beliefs that climate change is happening and at least partly human-caused. In turn, they overestimate the prevalence of skeptical views, namely that climate change is not happening and/or not human-caused. On average, people in our sample underestimate the prevalence of pro-climate views by at least ‑7.5% in Indonesia and up to ‑20.8% in Brazil. Despite these underestimations, people across the studied samples, on average, perceive the believing majority as a majority, reflecting relative rather than absolute pluralistic ignorance9.

Over ten years after pluralistic ignorance was first demonstrated in the context of climate change beliefs in an Australian sample4, we continue to see that people in a wide range of countries spanning four continents underestimate the prevalence of pro-climate views and overestimate the prevalence of skeptical views. However, while the original study found that Australians underestimated the prevalence of attribution skepticism (i.e., climate change is happening but not human-caused)—a rather prevalent opinion in Australia at that time (40.2%)—we hypothesize and demonstrate the reverse: People across all 11 countries substantially overestimate the size of this current minority group. These diverging results were expected because they align with the phenomenon of pluralistic ignorance, such that groups tend to underestimate the size of majority groups and overestimate the size of minority groups7–9. Alongside the scientific importance of these findings, this work highlights the significance of adapting hypotheses when the context changes. Thus, results of a replication study that are inconsistent with the original research can still constitute a successful replication if the new findings are consistent with the underlying phenomenon. Overall, pluralistic ignorance regarding climate change beliefs conceptually replicates across countries.

We observe noticeable differences across samples in terms of magnitude and presence of pluralistic ignorance, with people from Brazil and Poland showing the largest and people from Indonesia and India the smallest misperceptions. This pattern may be tentatively explained in terms of cultural tightness-looseness20. While countries high in cultural tightness, such as Indonesia and India46, have clearer social norms with strict sanctions for norm deviations, countries high in cultural looseness, such as Brazil and Poland46, have more ambiguous norms with more tolerance for deviations20. Pluralistic ignorance may be lower in culturally tight compared to culturally loose nations because (a) clearer norms make it easier to perceive these norms more accurately, and (b) stricter sanctions for deviations may motivate people to perceive existing norms correclty21. While we find a general tendency that higher cultural tightness is linked to lower misperceptions, this explanation is speculative, and we are cautious about overinterpreting variability between samples from different countries. For example, a recent study21 from China suggests that individuals in culturally tighter Eastern provinces do not perceive norms more correctly than those from culturally looser regions in West and Central China. However, as the authors note, this finding may not generalize to the country level, as within-country variation in cultural tightness-looseness tends to be smaller than between-country variation21. Therefore, future research might formally test this idea on data including larger samples from each country and a larger set of countries.

Besides widespread pluralistic ignorance, we find that providing information about country-specific public opinion on climate change makes climate change believers slightly more willing to express their opinion on climate change. In contrast to previous research12, we show that this effect—although very small in magnitude—may be present when providing real-world data about the actual distribution of climate change beliefs rather than fake data that people’s opinion on climate change is changing. This has practical implications for climate change communication: Communicating that many people in a country believe in human-caused climate change may boost discussions around the topic among people who do not know each other. These discussions are important because they can break the spiral of silence and thus potentially further reduce pluralistic ignorance surrounding climate change beliefs12,22. Although the effect is small (Cohen’s *d* = 0.05), it might still be of practical importance47 because the effect seems self-amplifying and the intervention easily scalable.

The social consensus intervention does not influence any of the other outcomes related to climate action (i.e., own willingness to change one’s lifestyle and support government action; expectations about fellow citizens’ willingness to change their lifestyle and support government action on climate change; and beliefs about citizens efficacy to contribute to reducing climate change). These results are somewhat surprising in light of the intervention’s intuitive appeal and given that prior social consensus interventions consistently show debiasing effects and subsequent effects on support for climate policies and pro-environmental behavior5,12,32,33. One potential explanation for the current results are saturation effects. Individuals’ estimates of others’ climate change beliefs are still somewhat inaccurate compared to the YouGov data presented in the intervention, but these differences are relatively small. As social consensus interventions are generally more effective when prior estimates are less accurate40, these small differences may have prevented individuals from markedly updating their expectations about others and consequently any further downstream effects on personal willingness to make lifestyle changes and support for government action.

Yet, the intervention was relatively ineffective even in samples with, on average, rather inaccurate beliefs. While social consensus messaging about climate change is emerging as an intervention approach on social media and as a part of online educational tools, its time may have passed. In the current climate of widespread media attention on climate change, communicating the public opinion on climate change may have left audiences who are relatively familiar with similar information largely unaffected. This is consistent with a recent German study48 where communicating the scientific consensus on climate change could only slightly increase perceived scientific agreement and had no cascading effects on climate change beliefs and policy support.

While this study contributes to understanding pluralistic ignorance regarding climate change beliefs and the value of social consensus messaging for climate action, we recognize several limitations that present fruitful avenues for future work. First, while the magnitude of misperceptions about others’ climate change beliefs substantially varies across country samples, we cannot formally test any potential explanations of this variation due to the relatively small number of countries included in this study. Future research using a larger cross-section of countries may be able to explore which country-level factors, such as cultural tightness-looseness and media coverage49, predict pluralistic ignorance in the context of climate change beliefs. The present study provides initial evidence that people in culturally tight rather than loose countries might predict others’ climate change beliefs more accurately. If these findings hold in samples with more countries, future research should also explore whether social consensus interventions of climate change beliefs are differently effective in culturally tight compared to culturally loose countries to reconcile two theoretical perspectives. Cultural tightness-looseness theory would predict that such interventions are more effective in tight cultures due to less tolerance for norm violation, stronger situations, and higher feelings of accountability50. In contrast, misperception correction approaches would predict that such interventions are more effective when people are less accurate40.

Second, the intervention design was limited by pre-existing cross-country data. This allowed for testing the effectiveness of an emerging, real-word intervention—communicating the social consensus on how many others believe in climate change. However, this intervention may not necessarily be the most effective approach. For example, communicating a stronger fake social norm (“67% of Americans are angry about the inaction of the US on climate change”) can boost support for climate policies more than a weaker fake social norm (“67% of Americans believe that climate change is mostly caused by human activity”)30. This calls for quantifying and updating different types of social consensus in a way that is consistent across countries. Richer secondary data about emerging consensuses would allow for selecting the most promising intervention based on several criteria: majority support for the norm, a significant underestimation of the actual consensus, and a significant association of misperceptions with the outcomes51.

Third, despite using cross-quota samples in terms of age and sex and reweighting the samples by climate change beliefs, fully representative samples would have been desirable. With the current samples, the findings seem to primarily generalize to urban and highly educated parts of the studied populations. However, previous research in the US suggests that demographics (i.e., highest completed level of education, gender, and household income) do not predict misperceptions of voters’ support for several environmental policies; one of the most important predictors is one’s own support for the policies52. Applied to our study, this might imply that one’s own climate change beliefs rather than demographic characteristics are most likely to predict pluralistic ignorance. We, therefore, reweighted the existing cross-quota samples (age and sex) to match the national parameters of climate change beliefs based on the YouGov Globalism survey1 to draw valid conclusions about pluralistic ignorance effects even in the absence of fully representative samples.

# Conclusion

Across a diverse set of 11 countries and 3,653 participants, we find broad generalizability for pluralistic ignorance in the context of climate change beliefs: People across all studied countries underestimate the prevalence of pro-climate views and consistently overestimate the prevalence of skeptical views in their country, with varying magnitudes. However, the results question the effectiveness of providing information about public opinion on climate change, except for potential effects on willingness to express one’s opinion on climate change. Despite being very small, these effects may still be an important precursor for breaking the spiral of silence. Given that climate change continues to rise up the agenda for media and public discourse, the overall results question the continued use of social consensus messages.

# Methods

To test the proposed hypotheses and research questions (Table 1), we conducted an online survey experiment across 11 countries. Prior to data collection, the hypotheses, research questions, sampling plan, study design, and data analyses were preregistered on PsychArchives (June 29, 2022; <http://dx.doi.org/10.23668/psycharchives.7059>) and peer-reviewed via the Lab Track program from the Leibniz Institute for Psychology (ZPID). We report how we determined the sample size, all data exclusions (if any), all manipulations, and all measures in the study53. Deviations from the preregistered protocol are in Supplement D. Materials in all languages are available on the OSF upon article publication.

## Participants

Participants were recruited through *respondi* (<https://www.respondi.com/access-panel>), an external panel provider certified under ISO 20252, from September 14 to October 13, 2022. For inclusion, participants needed to be at least 18 years old as well as citizens and residents of one of the 11 countries (Brazil, Canada, China, Germany, India, Indonesia, Italy, Japan, Mexico, Poland, or Thailand). Participants were compensated according to the panel’s standard criteria, with points that could be redeemed for money, a voucher, or a donation, depending on participants’ choice.

A total of 8,151 participants started the online survey experiment. Of these, 3,474 were screened out because the quota was already full (*n* = 3,369; 41.3%) or they were not eligible for this study (*n* = 105; 1.3%). An additional 533 participants were excluded because they failed the attention check (*n* = 80; 1.0%) or completed the survey experiment in under 3 minutes[[1]](#footnote-1) (*n* = 453; 5.6%). Moreover, 475 (5.8%) participants did not complete the survey experiment, and 16 (0.2%) were potential bots (reCAPTCHA < 0.5; not preregistered) and thus excluded. These exclusions resulted in an analytic sample of 3,653 participants across 11 countries.

Participants were, on average, 43.60 years old (*SD* = 15.79; range: 18-85 years), 1,839 (50.3%) were female, and 2,099 (57.5%) held a university degree. Most participants (*n* = 2,797; 76.6%) lived in urban areas. We applied cross-quota sampling considering age and sex, based on data from the OECD in 202054 and the National Statistical Office of Thailand in 202155. We reweighted the data by national climate change beliefs derived from the YouGov survey1. Weighted descriptive statistics by country and corresponding population statistics are in Table 4.

**Table 4**

*Descriptive Statistics by Country*

|  | **Weighted Cross-Quota Sample** | | | | | | | | | | | | **Population1** | | | **YouGov Globalism** | | | | | | | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Country |  | Mean Age (*SD*) | Female (%) | University degree (%) | Mean PO  (*SD*) | Mean NI  (*SD*) | Urban (%) | Mainly human-caused (%) | Partly human-caused (%) | Not human-caused (%) | No climate change (%) | Don’t know (%) | | University degree (%)2 | Urban (%)3 | | Mainly human-caused (%) | Partly human-caused (%) | Not human-caused (%) | No climate change (%) | | Don’t know (%) | |
| Brazil | 331 | 40.5 (14.8) | 51.5 | 55.5 | 5.8  (3.2) | 9.4  (1.4) | 96.6 | 55.0 | 33.0 | 5.0 | 4.0 | 3.0 | | 16.5 | 88 | | 55  ±3.07 | 33  ±2.90 | 5  ±1.34 | | 4  ±1.21 | | 3  ±1.05 | |
| Canada | 329 | 45.2 (16.1) | 49.7 | 61.1 | 4.9  (2.4) | 8.8  (1.7) | 73.7 | 39.0 | 44.0 | 8.0 | 3.0 | 6.1 | | 25.8 | 82 | | 39  ±2.99 | 44  ±3.04 | 8  ±1.66 | | 3  ±1.05 | | 7  ±1.57 | |
| China | 333 | 43.5 (15.3) | 49.0 | 82.5 | 5.1  (1.7) | 9.0  (1.7) | 95.1 | 24.0 | 66.7 | 2.4 | 2.1 | 4.8 | | 15.54 | 64 | | 23  ±2.59 | 64  ±2.95 | 5  ±1.34 | | 2  ±0.86 | | 5  ±1.34 | |
| Germany | 329 | 48.0 (16.5) | 50.0 | 32.3 | 5.0  (1.8) | 8.0  (2.0) | 58.8 | 31.7 | 53.2 | 8.2 | 2.0 | 4.9 | | 28.4 | 78 | | 31  ±2.83 | 52  ±3.06 | 8  ±1.66 | | 2  ±0.86 | | 7  ±1.56 | |
| India | 330 | 38.0 (14.8) | 48.2 | 81.8 | 6.3  (2.7) | 8.6  (2.7) | 80.7 | 51.0 | 27.0 | 11.0 | 5.0 | 6.0 | | 12.2 | 36 | | 51  ±3.00 | 27  ±2.66 | 11  ±1.88 | | 5  ±1.31 | | 6  ±1.42 | |
| Indonesia | 330 | 39.2 (14.7) | 49.2 | 58.5 | 6.2  (2.0) | 9.5  (1.1) | 80.1 | 31.2 | 42.6 | 17.0 | 3.1 | 6.1 | | 10.5 | 58 | | 30  ±2.75 | 41  ±2.95 | 18  ±2.30 | | 3  ±1.02 | | 8  ±1.63 | |
| Italy | 328 | 47.5 (15.5) | 51.9 | 36.2 | 4.9  (2.6) | 8.4  (2.1) | 70.8 | 47.1 | 41.0 | 6.1 | 2.0 | 3.7 | | 16.5 | 72 | | 46  ±2.67 | 40  ±2.63 | 6  ±1.27 | | 2  ±0.75 | | 6  ±1.27 | |
| Japan | 354 | 48.6 (16.1) | 50.3 | 54.6 | 5.0  (1.4) | 8.6  (1.9) | 48.9 | 36.4 | 49.5 | 5.0 | 2.0 | 7.1 | | 19.9 | 92 | | 36  ±2.95 | 49  ±3.07 | 5  ±1.34 | | 2  ±0.86 | | 7  ±1.57 | |
| Mexico | 328 | 39.5  (14.5) | 51.2 | 66.0 | 5.7  (2.7) | 9.3  (1.6) | 90.1 | 47.8 | 33.8 | 13.9 | 2.0 | 2.4 | | 17.1 | 81 | | 48  ±3.06 | 34  ±2.90 | 14  ±2.12 | | 2  ±0.86 | | 3  ±1.04 | |
| Poland | 330 | 45.5 (16.0) | 51.2 | 44.2 | 5.6  (2.8) | 8.6  (2.2) | 74.6 | 41.6 | 39.6 | 7.9 | 4.0 | 6.9 | | 23.15 | 60 | | 42  ±3.06 | 40  ±3.03 | 8  ±1.68 | | 4  ±1.21 | | 7  ±1.58 | |
| Thailand | 331 | 43.8 (14.5) | 51.5 | 59.3 | 5.1  (2.3) | 8.9  (1.9) | 74.8 | 42.0 | 37.0 | 10.0 | 5.0 | 6.0 | | 15.6 | 53 | | 42  ±3.02 | 37  ±2.96 | 10  ±1.84 | | 5  ±1.33 | | 6  ±1.45 | |
| Total | 3,653 | 43.6 (15.8) | 50.3 | 57.5 | 5.4  (2.4) | 8.9  (1.9) | 76.6 | 40.6 | 42.6 | 8.6 | 3.1 | 5.2 | |  |  | |  |  |  | |  | |  | |

*Note.* 1The population-level data are compiled from different years, countries, and sources, with varying definitions of the educational degree and urban areas. These data, therefore, only serve the purpose of comparisons with the samples in this study. 2Percentage of the population (25 years or older) that completed a Bachelor’s degree or equivalent based on data from the World Bank from 2010 to 2020, depending on the country56. 3Percentage of the total population living in urban areas based on data from the World Bank in 202257. 4 Source: Chinese government (2021) <https://www.gov.cn/guoqing/2021-05/13/content_5606149.htm>; 5Source: Statistics Poland (2021) <https://stat.gov.pl/spisy-powszechne/nsp-2021/nsp-2021-wyniki-wstepne/ludnosc-wedlug-cech-spolecznych-wyniki-wstepne-nsp-2021,2,1.html>.

The cross-quota samples regarding age and sex were stratified climate change beliefs based on the YouGov data. Levels of education range from 1 to 7, including 4 (Vocational school) and 5 (College or university: Bachelor or equivalent). PO = Political orientation, ranging from 0 *left* to 10 *right*. NI = National identification, ranging from 0 *strongly disagree* to 10 *strongly agree*. In some countries, the sample size deviates from the preregistered *n* = 330 because (a) a small number of potential bots were excluded (Canada, Germany, Italy, Japan, Mexico), (b) several participants completed the survey at the same time while the quota had just been reached (Brazil, China, Thailand), or the panel provider recruited an additional 10% due to potential bots (Japan). The ± values indicate the margins of error based on the 95% confidence interval calculated using the R package *moe* (Version 0.9.1)42.

## Sampling Plan

We ran a priori power simulations based on the original plan to fit frequentist fractional logistic regressions in each country. These simulations indicated that *n* = 300 per country allowed us to reliably detect (*p* < .01 and power ≥ 95%) very small effects of pluralistic ignorance (5% difference between perceived beliefs of others and actual beliefs). Previous research coded < 10% differences as accurate when estimating a dichotomous outcome (i.e., estimated percentage of how many fellow citizens should (not) get vaccinated)58. We conservatively set the threshold to 5% because participants in this study estimated five climate change beliefs—which reduces the effect—and lower levels of misperceptions are unlikely to be practically relevant. However, the results should be interpreted with caution, as we fit Bayesian multi-level zero-one-inflated regressions in the end, for which a priori power analyses are not possible to due computational constraints.

We did not conduct any a priori power analyses for the intervention effects, as the available computational resources do not allow for running several thousand Bayesian ordinal regression models. However, as we focus on overall effects across all 11 countries, 3,300 participants should suffice to reliably estimate and detect small but meaningful overall effects (for a similar argument, see59).

## Country Selection

We selected the 11 countries based on availability and geographic spread. First, we included only those countries that were available on the *respondi* online panel and where high-quality data on the distribution of climate change beliefs were available (i.e., countries in the YouGov Globalism survey) to present in the intervention. When selecting countries, we aimed for diversity in terms of climate change beliefs (i.e., the percentage of climate change believers ranged from 71% in Indonesia to 88% in Brazil; Table 5), cultural tightness-looseness, and geographic spread following recent calls to increase national diversity in psychology60. National diversity is pivotal for environmental psychology because climate change affects some regions and countries more than others61. For example, India (rank 7 in 2019), Japan (rank 4 in 2019), and Thailand (rank 9 from 2000-2019) are some of the most vulnerable countries around the globe in terms of extreme weather events. In contrast, Brazil, Canada, and Poland are comparably less affected by such events62. At the same time, most selected countries are understudied in (environmental) psychology. To draw conclusions about the more global versus local nature of pluralistic ignorance in the context of climate change beliefs, this study pays special attention to including countries that are usually understudied but disproportionately affected by climate change.

## Materials

Participants’ *climate change beliefs* were measured using one item adapted from the YouGov Globalism survey1: “In general, which of the following statements, if any, best describes your view?” Participants selected one of five statements, including “The climate is changing, and human activity is mainly responsible”, “The climate is changing, and human activity is partly responsible, together with other factors”, “The climate is changing but human activity is not responsible at all”, “The climate is not changing”, and “I don’t know.”

*National identification*(moderator) was measured with two statements: “I identify as [nationality]” and “Being a [nationality] is an important reflection of who I am”63, on an 11-point scale with three labels, 0 *strongly disagree*, 5 *neither agree nor disagree*, and 10 *strongly agree*. To create an overall national identification score, we averaged across the two items (τb = .56, 95% CrI [.53, .58], BF10 ∞).

*Perceived climate change beliefs of others* (outcome) were assessed using the following adapted item4,5: “What percentage of [country citizens], do you believe, would think the following ways about climate change? Please indicate a number from 0% (no one) to 100% (everyone) for the following statements such that they sum up to 100%.” Participants were then shown the five response categories of climate change beliefs. The survey software only allowed them to proceed if the percentages across the five categories summed up to 100%.

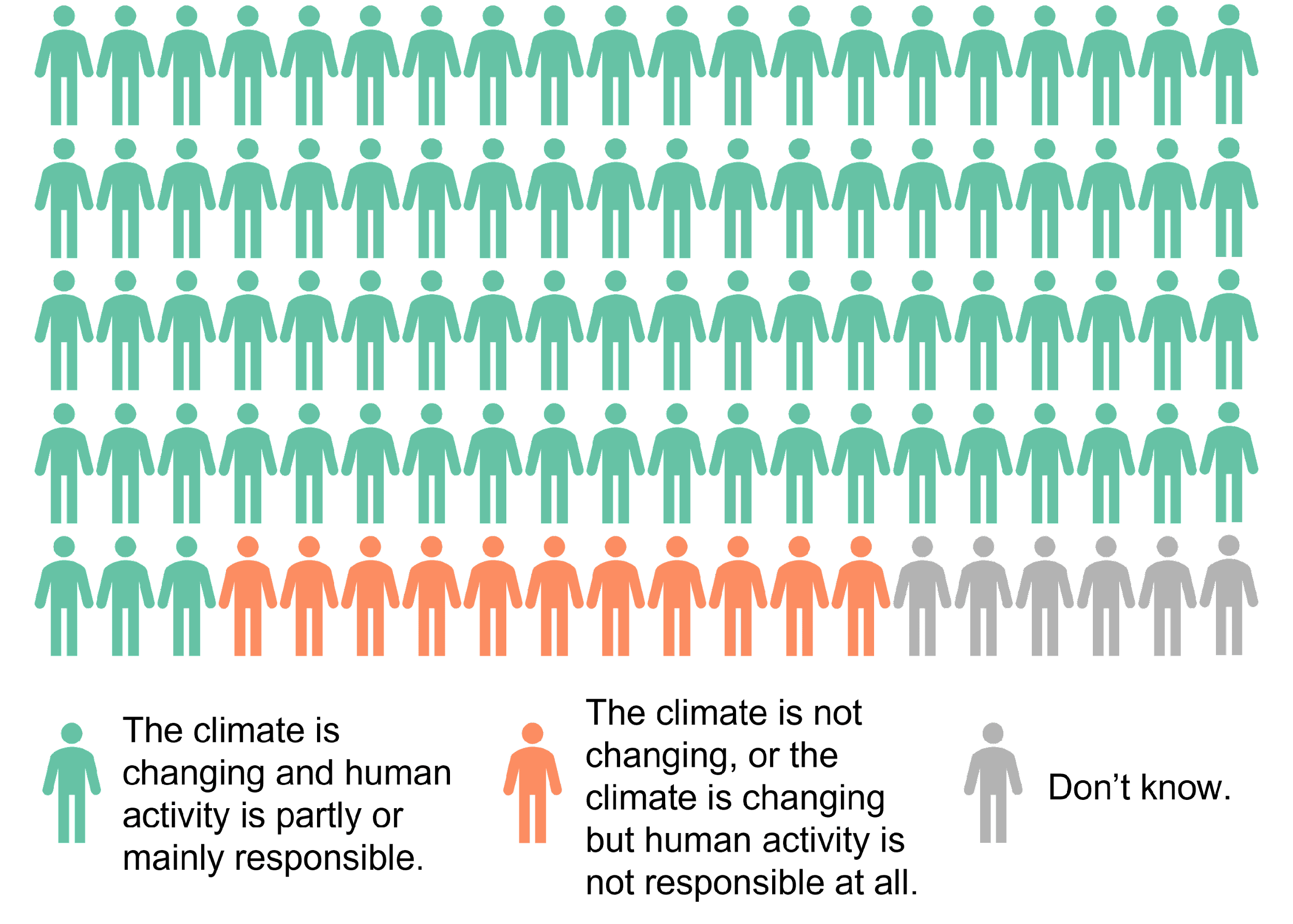
*Pluralistic ignorance regarding climate change beliefs* (outcome) was represented by an accuracy score—the difference between an individual’s belief of others’ climate change beliefs and the percentage of individuals holding the respective climate change belief in each country10. For example, if a Mexican participant estimated that 20% of Mexicans believe that the climate is not changing, but only 2% of our Mexican sample thought so, the participant’s score would be 18% (20%-2%).

The experimental manipulation consisted of either a *control* or *intervention message* adapted from previous studies40,64. In the control condition, participants were informed about their previous estimates: “Previously, you estimated that [x]% of [country citizens] believe that the climate is changing and human activity is partly ([x]%) or mainly ([x]%) responsible.” In the intervention condition, participants were presented with the following additional message and a graphic adapted to each country (Figure 4): “You might be interested to know that a recent survey showed that [x]% of [country citizens] believe that the climate is changing and human activity is partly ([x]%) or mainly ([x]%) responsible.” The distribution of beliefs was based on real-world data from the 25-country YouGov Globalism survey in 20201. The YouGov Globalism survey invited a random subsample from an online panel to participate in the survey between July 30 and August 24, 2020. The samples (*N* = 1,001-1,337) were representative of the country’s adult population (Brazil, Canada, Germany, Italy, Japan, Mexico, and Poland) or of the country’s online adult population (China, India, Indonesia, and Thailand) at least in terms of age, gender, and region65.

The strength of the descriptive norm thus varied across countries, as shown in Table 5, from 71% of Indonesians to 88% of Brazilians who believe in human-caused climate change. We decided to collapse the two categories of climate change believers (i.e., mainly and partly human-caused) to simplify the message and create a clear pro-climate social norm. We used real-world data for ethical reasons, to ensure the credibility of the message, and to test the effectiveness of the norm under realistic conditions (see comparable research58,64). While these real-world data were two years old at the time this study was conducted, they are consistent with opinion data collected on Facebook in 202266, both in terms of (a) the percentage of people per country who believe in human-caused climate change and (b) the order of these percentages per country (e.g., highest: European and Middle/South American countries; lowest: South-East Asian countries).

**Figure 4**

*Graphical Representation of the Intervention Message (Example: Canada, English version)*



*Note.* Icons created by Uniconlabs - Flaticon, <https://www.flaticon.com/free-icons/person>.

**Table 5**

*Actual Climate Change Beliefs by Country From the YouGov Globalism Survey (2020)*

|  |  |  |  |
| --- | --- | --- | --- |
| **Country** | **The climate is changing, and human activity is partly or mainly responsible.** | **The climate is not changing, or the climate is changing but human activity is not responsible at all.** | **Don’t know.** |
| Brazil | 88% | 9% | 3% |
| Canada | 83% | 11% | 6% |
| China | 87% | 7% | 6% |
| Germany | 83% | 10% | 7% |
| India | 78% | 16% | 6% |
| Indonesia | 71% | 21% | 8% |
| Italy | 86% | 8% | 6% |
| Japan | 85% | 7% | 8% |
| Mexico | 82% | 16% | 2% |
| Poland | 82% | 12% | 6% |
| Thailand | 79% | 15% | 6% |

*Note.* If the categories summed up to more than 100% due to rounding, we adjusted the percentage in the “Don’t know” category by ±1%.

Following Ruggeri et al.’s design64, which also presented participants’ with their previous estimates in the control and intervention message, we did not measure updated perceptions of others’ climate change beliefs as a *manipulation check* for several reasons: First, including such a manipulation check introduces demand effects67, resulting in participants satisfying the researchers’ expectations after seeing the consensus message rather than indicating their privately held updated beliefs68. Second, during a piloting phase that included a manipulation check (see also preregistration), the cognitive interviews with pilot participants indicated that they were confused about why they are first asked to indicate their estimates of others’ climate change beliefs, then presented with their previous estimates as part of the control and intervention message, and afterwards asked again to indicate their estimates. Their feedback suggested that Ruggeri’s et al.’s approach is most suitable and including the manipulation check could seriously jeopardize the internal validity of this specific study. Last, a manipulation check as a measure of updated consensus perceptions cannot distinguish between (a) participants who did not read the message and (b) those who did not update their beliefs because they, for example, did not find the message credible. To ensure high data quality, we use study completion time as a proxy for engagement with the intervention message69 (see Participants). As the study was brief, it is likely that those who did not engage with the message did not engage with the rest of the survey either and would therefore be flagged as speeders and excluded69.

To assess *willingness to express one’s opinion on climate change* (outcome) among fellow citizens, we used one item12: “How willing or unwilling are you to express your opinion on climate change among [country citizens] you don’t know?” Participants indicated their willingness on a 7-point scale from 1 *not at all willing* to 7 *very willing*.

*Expectations about others’ willingness to make lifestyle changes and support government action*(outcomes) were measured with two items: “For the following question, please consider what [country citizens] think about climate change. What percentage of [country citizens], do you believe, would be willing to make the following extent of changes to how they live and work to help reduce the potential effects of climate change?” and “For the following question, please consider what [country citizens] think about climate change. What percentage of [country citizens], do you believe, think climate change should be a low/medium or high/very high priority of the government of [country]?”, followed by “Please indicate a number from 0% (no one) to 100% (everyone).”

*Own willingness to make lifestyle changes and support government action*(outcomes) were measured with two items that have been used in previous international surveys66,70: “How much, if anything, would you be willing to change about how you live and work to help reduce the effects of climate change?” Response options included *no changes at all, a few changes, some changes,* and *a lot of changes*. “Do you think climate change should be a low, medium, high, or very high priority for the government of [country]?” Response options included *low, medium, high,* and *very high*.

*Perceived group efficacy*(outcome) was measured using one item71 and a 7-point scale from 1 *not at all* to 7 *very much*, with two additional options (*Don’t know* and *I don’t believe in (human-caused) climate change*): “To what extent do you think that [country citizens] can jointly prevent the negative consequences of climate change?”The original scale included three items. We selected one of the three items based on face validity and domain coverage due to the high reliability in previous research (Cronbach’s α = .9472) and thus repetitiveness of the full scale. Using the Spearman-Brown prediction formula73, the reliability of this shortened instrument was estimated to be very good (Cronbach’s α = 0.84).

Participants’ *attention* was checked at the end of the survey, using one item: “With this question, we would like to ensure that participants pay attention. Please select the option ‘Red’ from the list below.” Participants could select one of five options (*Blue*, *Red*, *Ytaellow*, *Green*, and *White*).

*Demographic information* included age (continuous; control variable), sex (female/male; control variable), citizenship and country of residence (yes/no; control variable), urbanicity (*urban*, *rural*, or *don’t know*), education (seven categories from 0 *no formal education* to 7 *doctoral degree*, adapted to each country; control variable), and political orientation74 (0 *left* to 10 *right;* control variable).

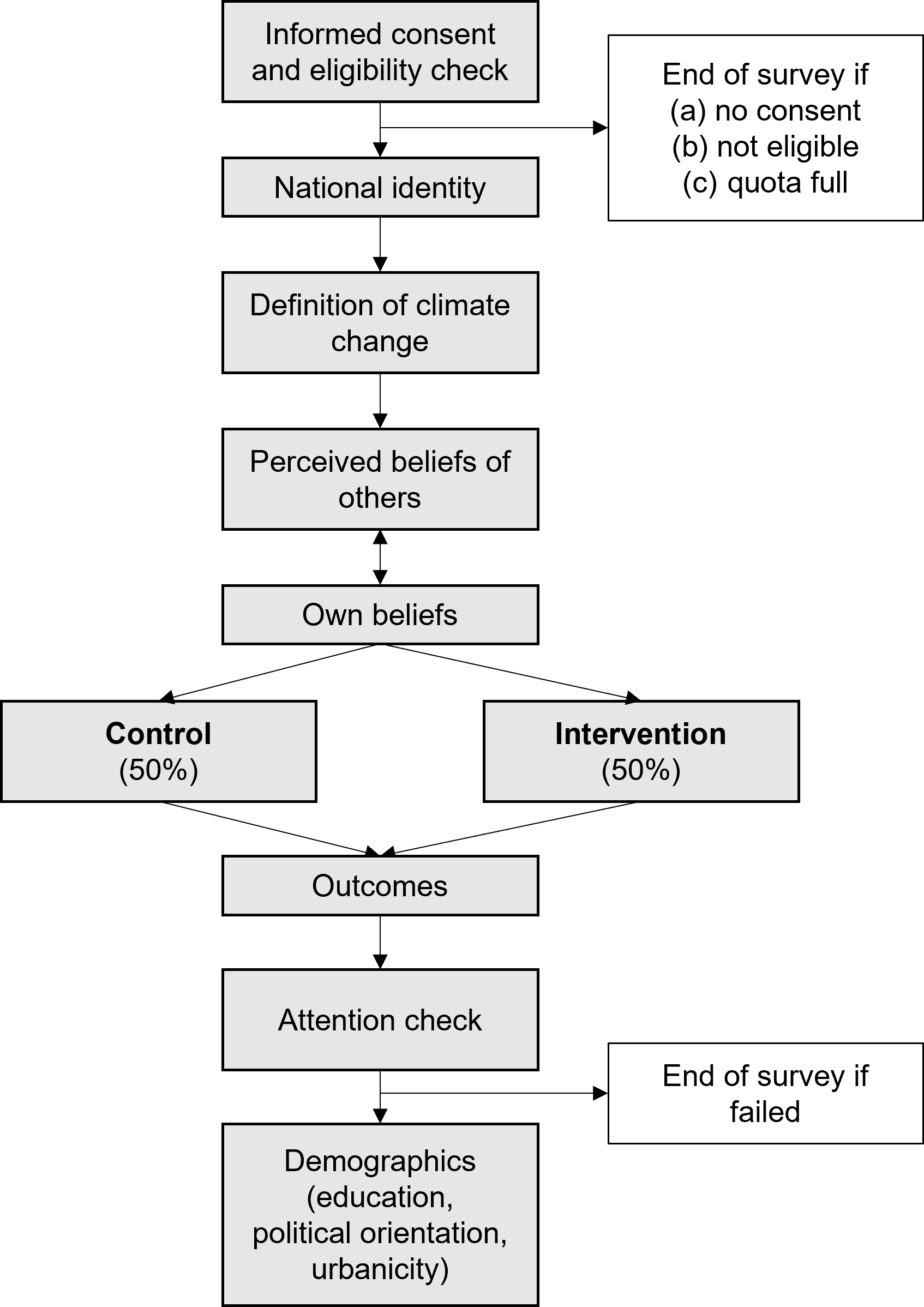
## Procedure

The study was approved by the ethics committee at the University of [blinded for review] (Project No. 00769 and No. 00843) and translated using a standard forward and back-translation approach (see Translation). Participants completed the survey administered on Qualtrics in the local language. After providing informed consent, they indicated their age and sex for the cross-quota sampling as well as their citizenship and country of residence for the eligibility checks. Participants who did not consent or were not citizens and residents of one of the 11 countries were redirected to the end of the survey. After participants answered the national identification items, they read a short description of climate change (“Climate change refers to the idea that the world’s average temperature has been increasing over the past 150 years, will increase more in the future, and that the world’s climate will change as a result.”75). They subsequently indicated their own climate change beliefs and perceptions of others’ climate change beliefs. The order was counterbalanced across participants, such that half of the participants per country first reported their own beliefs, whereas the other half first reported their perception of others’ beliefs.[[2]](#footnote-2) The order of the five belief categories was also counterbalanced across participants—either increasing or decreasing (from *not happening* to *mainly human-caused* or vice versa, with *don’t know* as a fixed fifth option).

Participants were then randomly but evenly assigned to the control or intervention condition and completed the six outcome measures in fixed order (i.e., willingness to express one’s opinion, expectations about others’ willingness to make lifestyle changes, own willingness to make lifestyle changes, expectations about others’ support for government action, own support for government action, and perceived group efficacy). Participants completed an attention check and were redirected to the end of the survey if they failed. Lastly, they provided their remaining demographics (i.e., education, political orientation, and urbanicity). The median time to complete the survey was 6.4 min. Figure 5 provides an overview of the study procedure.

**Figure 5**

*Overview of the Study Flow*



## Translation

Materials were translated using a standard forward and back-translation approach adapted from the Psychological Science Accelerator76,77. Materials were first translated from English to the local language by a native speaker and then back-translated by a second, independent native speaker. The back-translation was compared to the original English version, and disagreements were resolved through discussion between the two translators. The final version was proofread in terms of clarity and comprehensibility by several individuals from the target population. Country-specific deviations are listed in Supplement E.

## Data Analysis

### Weighting

For each country, we collected cross-quota samples based on age and sex. We additionally used post-stratification raking (R package *anesrake*, Version 0.8078) to align the sample distribution of climate change beliefs with the data from the YouGov Globalism survey1 and ensure adequate representation of all climate change belief groups. The algorithm iteratively adjusts the weight of each case until the marginal distribution of climate change beliefs as well as the joint distribution of age and sex in the samples align with the specified population targets based on data from the OECD (2020)54, the National Statistical Office of Thailand (2021)55, and the YouGov Globalism survey1. As in the European Social Survey79, weights were trimmed at 4.0 for Canada, China, Germany, Indonesia, Italy, and Mexico to reduce the effect of outliers. For all other countries (i.e., Brazil, India, Japan, Poland, and Thailand), weight trimming was not necessary. These weights were only used in the analyses regarding pluralistic ignorance effects (Hypotheses 1a-d), as the other analyses (Hypotheses 3-6) only concerned climate change believers.

### Models

All analyses were conducted in *R* (Version 4.1.0)80 and *brms* (Version 2.16.3)81 using *RStan* (2.21.3)82. Deviations from the preregistration are reported in Supplement D. As detailed in the preregistration, we use a Bayesian approach to data analysis—whenever possible—to be able to quantify the relative support for or against any potential effects and to communicate this gradual evidence in an easy-to-understand way83. For Hypotheses 1a-d and Research Question 1, we fitted Bayesian multi-level regression models (level 1: participants, level 2: countries) with perceived percentages of each of the four climate change belief categories (i.e., mainly human-caused, partly human-caused, not human-caused, and no climate change) as outcomes. We used zero-one inflated regressions to model the doubly bounded data in the interval from 0 (0%) to 1 (100%). Priors were weakly informative defaults, with α, γ ~ logistic(0, 1) for the probability of an observation being a 0 or 1 (α) and the probability of an observation being a 1 given that it is either 0 or 1 (γ), μ, ϕ ~ Student t(3, 0, 2.5) for mean (μ) and precision (ϕ) parameter of the beta distribution, as well as var ~ Student t(3, 0, 2.5) for all variance parameters.

To test the intervention’s effectiveness, we estimated Bayesian multi-level cumulative probit regressions for ordinal data (Hypotheses 3, 4a, 5a, and Research Question 2) and frequentist fractional logistic regression with country as a fixed predictor for 0-100% data (Hypotheses 4b and 5b). We controlled for age, sex, education, and political orientation if they were associated with the outcome. For the cumulative probit models, we used uniform priors on the threshold parameters and weakly informative priors for the predictor coefficients, *b* ~ Normal(0, 10), and all variances, *var* ~ HalfNormal(0, 1).

All Bayesian models were fitted with four chains, each with 20,000 iterations, of which 5,000 per chain served as a warm-up. Posterior convergence is evaluated based on trace plots, values (< 1.05), the effective sample size (> 1,000 for stable estimates84), and divergent transitions. Model fit is assessed based on posterior predictive checks.

### Decision Rules

Conclusions regarding the hypotheses and research questions are based on the posterior distribution, credible intervals, and the Bayes factor, including its standard inference criteria (Supplement B). Credible intervals (CrIs) indicate that the true population estimate would fall within this interval with a certain probability (one-sided tests: 90%; two-sided tests: 95%), given the priors and the observed data85. The Bayes factor (BF) quantifies the strength of evidence in favor of a hypothesis over another hypothesis86. In the current paper, BF10 and BF01 indicate two-sided testing of two competing hypotheses—that the effect differs from zero (H1) and that the effect is exactly zero (H0). For example, BF10 = 10 would indicate that the data are ten times more likely under H1 than H0,whereas BF01 = 10 would mean that the data are ten times more likely under H0 than H1. In contrast, BF+- and BF-+ indicate one-sided testing of two competing hypotheses—that the effect is positive (H+) and that the effect is negative (H-). Therefore, BF+- = 10 would mean that the data are ten times more likely under H+than H-, whereas BF-+ = 10 would indicate the opposite.

For drawing conclusions about pluralistic ignorance effects, we additionally use the region of practical equivalence (ROPE)43,44. This allows usto not only test whether the perceived percentages in our samples are *exactly* equal to the actual percentages in the YouGov survey1 but also whether they are equal to a range of actual percentages (i.e., practically equivalent). We define the ROPE as the actual percentages of climate change beliefs in the YouGov survey ± the sampling uncertainty as indicated by the margins of error based on 95% confidence intervals. These additional analyses have not been pre-registered.

# References

1. YouGov Cambridge. *Globalism 2020: Climate and lifestyle after COVID*. https://docs.cdn.yougov.com/rhokagcmxq/Globalism2020%20Guardian%20Climate%20and%20Lifestyle%20after%20COVID.pdf (2020).

2. Ballew, M. T. *et al.* *Americans underestimate how many others in the U.S. think global warming is happening.* https://climatecommunication.yale.edu/publications/americans-underestimate-how-many-others-in-the-u-s-think-global-warming-is-happening/ (2019).

3. Ban Rohring, E. J. & Akerlof, K. L. Perceptions of social consensus at the regional level relate to prioritization and support of climate policy in Maryland, USA. *Regional Environmental Change* **20**, 1–13 (2020).

4. Leviston, Z., Walker, I. & Morwinski, S. Your opinion on climate change might not be as common as you think. *Nat. Clim. Change* **3**, 334–337 (2013).

5. Mildenberger, M. & Tingley, D. Beliefs about climate beliefs: The importance of second-order opinions for climate politics. *Br. J. Polit. Sci.* **49**, 1279–1307 (2019).

6. Ballew, M. T. *et al.* Beliefs about others’ global warming beliefs: The role of party affiliation and opinion deviance. *J. Environ. Psychol.* **70**, Article 101466 (2020).

7. Prentice, D. A. & Miller, D. T. Pluralistic ignorance and alcohol use on campus: Some consequences of misperceiving the social norm. *J. Pers. Soc. Psychol.* **64**, 243–256 (1993).

8. O’Gorman, H. The discovery of pluralistic ignorance: An ironic lesson. *J. Hist. Behav. Sci.* **22**, 333–347 (1986).

9. Korte, C. Pluralistic ignorance about student radicalism. *Sociometry* 576–587 (1972).

10. Sargent, R. H. & Newman, L. S. Pluralistic ignorance research in psychology: A scoping review of topic and method variation and directions for future research. *Rev. Gen. Psychol.* **25**, 163–184 (2021).

11. Shamir, J. & Shamir, M. Pluralistic ignorance across issues and over time: Information cues and biases. *Public Opin. Q.* 227–260 (1997).

12. Geiger, N. & Swim, J. K. Climate of silence: Pluralistic ignorance as a barrier to climate change discussion. *J. Environ. Psychol.* **47**, 79–90 (2016).

13. Kjeldahl, E. M. & Hendricks, V. F. The sense of social influence: Pluralistic ignorance in climate change. *EMBO Rep.* **19**, e47185 (2018).

14. Rahmstorf, S. The climate skeptics. in *Weather catastrophes and climate change—Is there still hope for us?* 70–75 (pg-verlag, 2005).

15. Marks, G. & Miller, N. Ten years of research on the false-consensus effect: An empirical and theoretical review. *Psychol. Bull.* **102**, 72–90 (1987).

16. Ross, L., Greene, D. & House, P. The “false consensus effect”: An egocentric bias in social perception and attribution processes. *J. Exp. Soc. Psychol.* **13**, 279–301 (1977).

17. Baer, H. A. & Burgmann, V. *Climate politics and the climate movement in Australia*. (Melbourne Univ. Publishing (MUP) Academic, 2012).

18. Pew Research Center. *Climate change remains top global threat across 19-country survey*. 1–47 https://www.pewresearch.org/global/wp-content/uploads/sites/2/2022/08/PG\_2022.08.31\_Global-Threats\_FINAL.pdf (2022).

19. McCright, A. M. & Dunlap, R. E. The politicization of climate change and polarization in the American public’s views of global warming, 2001–2010. *Sociol. Q.* **52**, 155–194 (2011).

20. Gelfand, M. J., Nishii, L. H. & Raver, J. L. On the nature and importance of cultural tightness-looseness. *J. Appl. Psychol.* **91**, 1225–1244 (2006).

21. Chen, S., Wan, F. & Yang, S. Normative misperceptions regarding pro-environmental behavior: Mediating roles of outcome efficacy and problem awareness. *J. Environ. Psychol.* **84**, 101917 (2022).

22. Noelle-Neumann, E. *The spiral of silence: Public opinion–Our social skin*. (University of Chicago Press, 1993).

23. Yeager, D. S., Krosnick, J. A., Visser, P. S., Holbrook, A. L. & Tahk, A. M. Moderation of classic social psychological effects by demographics in the US adult population: New opportunities for theoretical advancement. *J. Pers. Soc. Psychol.* **117**, e84 (2019).

24. Boon-Falleur, M., Grandin, A., Baumard, N. & Chevallier, C. Leveraging social cognition to promote effective climate change mitigation. *Nat. Clim. Change* **12**, 332–338 (2022).

25. Goldberg, M. H., van der Linden, S., Leiserowitz, A. & Maibach, E. Perceived social consensus can reduce ideological biases on climate change. *Environ. Behav.* **52**, 495–517 (2020).

26. Wood, A. https://twitter.com/alainamwood/status/1557378818083520516 (2022).

27. Gapminder. Worldview upgrader: UN goal 13 climate action. https://upgrader.gapminder.org/t/sdg-world-13/.

28. Bursztyn, L. & Yang, D. Y. Misperceptions about others. *Annu. Rev. Econ.* **14**, (2021).

29. Andre, P., Boneva, T., Chopra, F. & Falk, A. Fighting climate change: The role of norms, preferences, and moral values. Preprint at https://docs.iza.org/dp14518.pdf (2021).

30. Sabherwal, A., Pearson, A. R. & Sparkman, G. Anger consensus messaging can enhance expectations for collective action and support for climate mitigation. *J. Environ. Psychol.* **76**, e101640 (2021).

31. Chan, H.-W., Udall, A. M. & Tam, K.-P. Effects of perceived social norms on support for renewable energy transition: Moderation by national culture and environmental risks. *J. Environ. Psychol.* **79**, 101750 (2022).

32. Jachimowicz, J. M., Hauser, O. P., O’Brien, J. D., Sherman, E. & Galinsky, A. D. The critical role of second-order normative beliefs in predicting energy conservation. *Nat. Hum. Behav.* **2**, 757–764 (2018).

33. Cole, J. C., Ehret, P. J., Sherman, D. K. & Van Boven, L. Social norms explain prioritization of climate policy. *Clim. Change* **173**, 1–21 (2022).

34. de Groot, J. I., Bondy, K. & Schuitema, G. Listen to others or yourself? The role of personal norms on the effectiveness of social norm interventions to change pro-environmental behavior. *J. Environ. Psychol.* **78**, 101688 (2021).

35. Sokoloski, R., Markowitz, E. M. & Bidwell, D. Public estimates of support for offshore wind energy: False consensus, pluralistic ignorance, and partisan effects. *Energy Policy* **112**, 45–55 (2018).

36. Tajfel, H. & Turner, J. C. The social identity theory of intergroup behavior. in *Political psychology* 276–293 (Psychology Press, 2004).

37. Stok, F. M., Verkooijen, K. T., de Ridder, D. T. D., de Wit, J. B. F. & de Vet, E. How norms work: Self-identification, attitude, and self-efficacy mediate the relation between descriptive social norms and vegetable intake. *Appl. Psychol. Health Well-Being* **6**, 230–250 (2014).

38. Liu, J., Thomas, J. M. & Higgs, S. The relationship between social identity, descriptive social norms and eating intentions and behaviors. *J. Exp. Soc. Psychol.* **82**, 217–230 (2019).

39. Cialdini, R. B. & Jacobson, R. P. Influences of social norms on climate change-related behaviors. *Curr. Opin. Behav. Sci.* **42**, 1–8 (2021).

40. Lees, J. & Cikara, M. Inaccurate group meta-perceptions drive negative out-group attributions in competitive contexts. *Nat. Hum. Behav.* **4**, 279–286 (2020).

41. van Stekelenburg, A., Schaap, G., Veling, H., van ’t Riet, J. & Buijzen, M. Scientific-consensus communication about contested science: A preregistered meta-analysis. *Psychol. Sci.* 9567976221083219 (2022) doi:10.1177/09567976221083219.

42. Dahlgren, P. moe: Calculate Margin of Error for Simple Probability Samples. (2023).

43. Makowski, D., Ben-Shachar, M. S. & Lüdecke, D. bayestestR: Describing effects and their uncertainty, existence and significance within the Bayesian framework. *J. Open Source Softw.* **40**, 1541 (2019).

44. Kruschke, J. K. Rejecting or accepting parameter values in Bayesian estimation. *Adv. Methods Pract. Psychol. Sci.* **1**, 270–280 (2018).

45. Jeffreys, H. *Theory of probability*. vol. 432 (Oxford University Press, 1961).

46. Gelfand, M. J. *et al.* The relationship between cultural tightness–looseness and COVID-19 cases and deaths: A global analysis. *Lancet Planet. Health* **5**, e135–e144 (2021).

47. Anvari, F. *et al.* Not all effects are indispensable: Psychological science requires verifiable lines of reasoning for whether an effect matters. *Perspect. Psychol. Sci.* Article 17456916221091565 (2022) doi:10.1177/17456916221091565.

48. Tschötschel, R., Schuck, A., Schwinges, A. & Wonneberger, A. Climate change policy support, intended behaviour change, and their drivers largely unaffected by consensus messages in Germany. *J. Environ. Psychol.* **76**, e101655 (2021).

49. Sparkman, G., Geiger, N. & Weber, E. U. Americans experience a false social reality by underestimating popular climate policy support by nearly half. *Nat. Commun.* **13**, 4779 (2022).

50. Gelfand, M. J. *et al.* Differences between tight and loose cultures: A 33-nation study. *Science* **332**, 1100–1104 (2011).

51. Constantino, S. M. *et al.* Scaling up change: A critical review and practical guide to harnessing social norms for climate action. *Psychol. Sci. Public Interest* **23**, 50–97 (2022).

52. Lees, J., Colaizzi, G., Goldberg, M. H. & Constantino, S. M. Misperceptions of Support for Climate Policy Represent Multiple Phenomena Predicted by Different Factors Across Intergroup Boundaries. Preprint at https://doi.org/10.31219/osf.io/vfbq4 (2023).

53. Simmons, J. P., Nelson, L. D. & Simonsohn, U. A 21 word solution. *Soc. Sci. Res. Netw.* 1–4 (2012).

54. Organisation for Economic Co-Operation and Development (OECD). Population projections. (2020).

55. National Statistical Office. Demography population and housing branch. (2021).

56. World Bank. World development indicators: Educational attainment, at least Bachelor’s or equivalent, population 25+, total (%) (cumulative) from 2010 to 2020. (2022).

57. World Bank. World development indicators: Urban population (% of total population). (2022).

58. Carey, J. M. *et al.* Minimal effects from injunctive norm and contentiousness treatments on COVID-19 vaccine intentions: evidence from 3 countries. *PNAS Nexus* **1**, pgac031 (2022).

59. Hoogeveen, S. *et al.* The Einstein effect provides global evidence for scientific source credibility effects and the influence of religiosity. *Nat. Hum. Behav.* **6**, 523–535 (2022).

60. Tam, K.-P. & Milfont, T. L. Towards cross-cultural environmental psychology: A state-of-the-art review and recommendations. *J. Environ. Psychol.* **71**, 101474 (2020).

61. King, A. D. & Harrington, L. J. The inequality of climate change from 1.5 to 2°C of global warming. *Geophys. Res. Lett.* **45**, 5030–5033 (2018).

62. Eckstein, D., Künzel, V. & Schäfer, L. *Global climate risk index 2021: Who suffers most from extreme weather events? Weather-related loss events in 2019 and 2000-2019*. https://www.germanwatch.org/en/cri (2021).

63. Van Bavel, J. J. *et al.* National identity predicts public health support during a global pandemic. *Nat. Commun.* **13**, 517 (2022).

64. Ruggeri, K. *et al.* The general fault in our fault lines. *Nat. Hum. Behav.* **5**, 1369–1380 (2021).

65. Buckle, J. YouGov Globalism Survey 2020 [personal communication]. (2022).

66. Leiserowitz, A. *et al.* *International Public Opinion on Climate Change*. https://climatecommunication.yale.edu/publications/international-public-opinion-on-climate-change/ (2021).

67. Rode, J. B., Iqbal, S., Butler, B. J. & Ditto, P. H. Using a News Article to Convey Climate Science Consensus Information. *Sci. Commun.* **43**, 651–673 (2021).

68. Lewandowsky, S., Gignac, G. E. & Vaughan, S. The pivotal role of perceived scientific consensus in acceptance of science. *Nat. Clim. Change* **3**, 399–404 (2013).

69. Lunz Trujillo, K., Motta, M., Callaghan, T. & Sylvester, S. Correcting Misperceptions about the MMR Vaccine: Using Psychological Risk Factors to Inform Targeted Communication Strategies. *Polit. Res. Q.* **74**, 464–478 (2021).

70. Bell, J., Poushter, J., Fagan, M. & Huang, C. *In response to climate change, citizens in advanced economies are willing to alter how they live and work*. 1–42 https://www.pewresearch.org/global/2021/09/14/in-response-to-climate-change-citizens-in-advanced-economies-are-willing-to-alter-how-they-live-and-work/ (2021).

71. van Zomeren, M., Spears, R. & Leach, C. W. Experimental evidence for a dual pathway model analysis of coping with the climate crisis. *J. Environ. Psychol.* **30**, 339–346 (2010).

72. van Zomeren, M., Leach, C. W. & Spears, R. Does group efficacy increase group identification? Resolving their paradoxical relationship. *J. Exp. Soc. Psychol.* **46**, 1055–1060 (2010).

73. Dahlke, J. A. & Wiernik, B. M. psychmeta: An R package for psychometric meta-analysis. *Appl. Psychol. Meas.* **43**, 415–416 (2019).

74. McMeel, O. *et al.* Seas, oceans and public health in Europe (SOPHIE; https://doi.org/10.5255/UKDA-SN-8972-1). (2019).

75. Maibach, E. *et al.* *A national survey of Republicans and Republican-leaning Independents on energy and climate change*. 1–12 https://climatecommunication.yale.edu/publications/republican-views-on-climate-change/ (2013).

76. Forscher, P. S., Paris, B., Primbs, M. & Coles, N. A. PSACR: The Psychological Science Accelerator’s COVID-19 rapid-response project. Preprint at https://doi.org/10.31234/osf.io/x976j (2020).

77. Jarke, H. *et al.* A roadmap to large-scale multi-country replications in psychology. *Collabra Psychol.* **8**, 57538 (2022).

78. Pasek, J. anesrake: ANES raking implementation. (2018).

79. Vehovar, V., Slavec, A. & Berzelak, N. Appendix: Data files and procedure used for weighting R1-R6. (2014).

80. R Core Team. R: A language and environment for statistical computing. (2021).

81. Bürkner, P.-C. Advanced Bayesian multilevel modeling with the R package brms. *R J.* **10**, 395–411 (2018).

82. Stan Development Team. RStan: The R interface to Stan. (2022).

83. Quintana, D. S. & Williams, D. R. Bayesian alternatives for common null-hypothesis significance tests in psychiatry: a non-technical guide using JASP. *BMC Psychiatry* **18**, 178 (2018).

84. Bürkner, P.-C. & Vuorre, M. Ordinal regression models in psychology: A tutorial. *Adv. Methods Pract. Psychol. Sci.* **2**, 77–101 (2019).

85. Hespanhol, L., Vallio, C. S., Costa, L. M. & Saragiotto, B. T. Understanding and interpreting confidence and credible intervals around effect estimates. *Braz. J. Phys. Ther.* **23**, 290–301 (2019).

86. Hoijtink, H., Mulder, J., van Lissa, C. & Gu, X. A tutorial on testing hypotheses using the Bayes factor. *Psychol. Methods* **24**, 539–556 (2019).

87. Lieberoth, A. *et al.* Stress and worry in the 2020 coronavirus pandemic: Relationships to trust and compliance with preventive measures across 48 countries in the COVIDiSTRESS global survey.

# Supplement A

**Comparison of the Original Study and the Present Replication Study**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Comparison Dimension** | **Original Study** | **Present Replication Study** | | **Reason for Change** | |
| **Hypotheses** | The original study found that the number of attribution skeptics (i.e., climate change is happening but not human-caused) is underestimated (perceived: 23.7% vs. actual: 40.2% in 2010). | Individuals overestimate the number of (c) attribution and (d) trend skeptics in their country. | | We expected that the number of attribution skeptics would be overestimated because descriptive evidence shows that attribution skeptics are a minority of 5% (Brazil, China, and Japan) to 18% (Indonesia) in all countries of interest1. This updated hypothesis is consistent with findings from later US studies on misperceptions of climate change beliefs5. | |
| **Sample** |  |  | |  | |
| Sample nature | Nationally representative sample of Australians (T1: 48.8% women; > 24-85+ years; 86% in urban area) | Cross-quota sample based on age and sex for each of the 11 countries (50.4% women, 18-85 years with *M* = 43.7; 77.3% in urban areas) | |  | |
| Sample size | *N* = 5,036  two waves | *N* = 3,652  one wave | | We used a smaller sample size to make the data collection feasible across as many countries as possible. This sample size, nevertheless, allowed us to reliably detect very small pluralistic ignorance effects of 5%. | |
| Recruitment | Accredited online panel provider | Accredited online panel providers | |  | |
| Mode of data collection | Online | Online | |  | |
| **Design** |  |  | |  | |
| Own climate change beliefs | Which of the following statements best describes your thoughts on climate change?   * I don’t think that climate change is happening. * I have no idea whether climate change is happening or not. * I think that climate change is happening, but it’s just a natural fluctuation in Earth’s temperatures. * I think that climate change is happening, and I think that humans are largely causing it.   The display order of the options was fixed, as shown above. | In general, which of the following statements, if any, best describes your view?   * The climate is changing, and human activity is mainly responsible. * The climate is changing, and human activity is partly responsible, together with other factors. * The climate is changing but human activity is not responsible at all. * The climate is not changing. * I don’t know.   The display order of the options was counterbalanced across participants:   1. Mainly human-caused Partly human-caused Not human-caused No climate change Don’t know 2. No climate change Not human-caused Partly human-caused Mainly human-caused Don’t know | | We used a measure previously employed in the multi-country YouGov Globalism survey, with five rather than four response options. We used this measure to (a) capture widely held beliefs that climate change is caused by both natural processes and human activity (27-64% depending on the country1), (b) test a social consensus intervention—which uses pre-existing, real-world data on the actual distribution of climate change beliefs in each of the studied countries, and (c) to compare the perceived beliefs of others against the actual beliefs from the large-scale YouGov survey as a robustness check. The content of our categories closely matches the content of the four original categories (see color coding of the items), though the wording differs. We believe that the fifth category is important since climate change beliefs have become more nuanced (not just natural vs. human-caused), as is indicated by the YouGov data, where this belief in partly natural, partly human-caused climate change is the most popular or second most popular belief in each of the 11 studied countries.  We also decided to vary the response order in which the response options are displayed, since we do not know whether and how the order of response options affects second-order beliefs. | |
|  |  | |  | |  | |
| Perceptions of others’ climate change beliefs | Try and guess the percentage of Australians who would think the following ways about climate change (HINT: the numbers you place beside all four boxes should add up to 100). The survey logic was set up in a way that participants could only proceed if the numbers added up to 100%.  The display order of the options was fixed (see own climate change beliefs). | | What percentage of [country citizens], do you believe, would think the following ways about climate change? Please indicate a number from 0% (no one) to 100% (everyone) for the following statements such that they sum up to 100%.”  The display order of the options was counterbalanced across participants (see own climate change beliefs). | | We adapted the wording to   1. reflect that we are interested in participants’ beliefs rather than implying that there is a correct answer, and their guess should get as close as possible (“try and guess”) to this correct answer. 2. help participants understand better what 0% and 100% imply. 3. match the slider scale we used. | |
| Attention check and bot detection | No information. | | With this question, we would like to ensure that participants pay attention. Please select the option ‘Red’ from the list below.  *Blue, Red, Yellow, Green,* and *White* | | To ensure high data quality, we added an attention check and reCAPTCHA bot detection. We added the attention check at the end of the survey, before the demographics, to avoid the check influencing the results. | |
| Additions | Second wave to test the stability of beliefs | | Intervention to causally test whether informing people about the actual beliefs in their country affects factors related to climate action. | | Since disclosing the actual beliefs on climate change is increasingly used as an intervention in the real world, we believe that testing what outcomes the intervention can affect is more valuable than replicating the stability of beliefs. | |

# Supplement B

**Standard Inference Criteria for Bayes Factors**

|  |  |  |  |
| --- | --- | --- | --- |
| **BF10**  **Evidence for H1** | **Interpretation** | **BF01**  **Evidence for H0** | **Interpretation** |
| ≥ 100 | The effect is *extremely* supported by the evidence. | ≥ 100 | The null effect is *extremely* supported by the evidence. |
| 30 ≤ BF10 < 100 | The effect is *very strongly* supported by the evidence. | 30 ≤ BF01 < 100 | The null effect is *very*  *strongly* supported by the evidence. |
| 10 ≤ BF10 < 30 | The effect is *strongly* supported by the evidence. | 10 ≤ BF01 < 30 | The null effect is *strongly* supported by the evidence. |
| 3 ≤ BF10 < 10 | The effect is *moderately* supported by the evidence. | 3 ≤ BF01 < 10 | The null effect is *moderately* supported by the evidence. |
| 1 < BF10 < 3 | The evidence is *insufficient* to make a decisive decision, although the effect likely exists. | 1 < BF01 < 3 | The evidence is *insufficient* to make a decisive decision, although the null effect likely exists. |
| 1 | No evidence | 1 | No evidence |

*Note.* Adapted from Lieberoth et al.87 and interpretation based on Jeffreys45.

# Supplement C

**Additional Analyses**

We additionally test (a) whether the results change without control variables (Table C1) and (b) whether the intervention is effective among climate change believers who previously underestimated the social consensus in their country (Table C2).

**Table C1**

*Results Without Control Variables*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Hypothesis /**  **Research question** | **Estimate  [90-95% CrI]** | **Bayes factor / p-value** | **Evidence in favor of / against Hypothesis** | **Comparison to main findings** |
| **H3:** willingness to express one’s opinion on climate change | 0.04  [-0.03, 0.11] | 5.63 | Moderate ●●○○○ | Consistent in terms of direction and magnitude of the effect as well as Bayes factor |
| **H4a:** own willingness to change lifestyle | -0.02  [-0.10, 0.07] | 217.25 | Extremely strong ●●●●● | Consistent in terms of direction and magnitude of the effect as well as the Bayes factor |
| **H4b:** expectations about others’ willingness to change their lifestyle | 1.41% | .087 |  | Consistent in terms of direction and magnitude of the effect as well as *p*-value |
| **H5a:** own support for government action | -0.01 [-0.10, 0.07] | 235.76 | Extremely strong ●●●●● | Consistent in terms of direction and magnitude of the effect as well as the Bayes factor |
| **H5b:** expectations about others’ government support | 1.35% | .094 |  | Consistent in terms of direction and magnitude of the effect as well as *p*-value |
| **RQ2:** group efficacy beliefs | -0.02  [-0.11, 0.07] | 211.74 | Extremely strong ●●●●● | Consistent in terms of direction and magnitude of the effect as well as the Bayes factor |

*Note.*CrI = credible interval.Insufficient evidence: ○○○○○; weak evidence: ●○○○○; moderate evidence: ●●○○○; strong evidence: ●●●○○; very strong evidence: ●●●●○; extremely strong evidence:●●●●●. Blue indicates evidence in favor of the tested hypothesis or research question; red indicates evidence against it.

**Table C2**

*Effectiveness of the Intervention Among Climate Change Believers who Underestimated the Social Consensus Prior to the Intervention*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Hypothesis /**  **Research question** | **Estimate  [90-95% CrI]** | **Bayes factor / p-value** | **Evidence in favor of / against Hypothesis** | **Comparison to main findings** |
| **H3:** willingness to express one’s opinion on climate change | 0.03  [-0.06, 0.11] | 2.45 | Weak ●○○○○ | Consistent in terms of direction and magnitude of the effect but slightly lower Bayes factor |
| **H4a:** own willingness to change lifestyle | -0.02  [-0.14, 0.11] | 158.48 | Extremely strong ●●●●● | Consistent in terms of direction and magnitude of the effect as well as the Bayes factor |
| **H4b:** expectations about others’ willingness to change their lifestyle | 1.83% | .049 |  | Slightly—although not meaningfully—larger and now significant effect |
| **H5a:** own support for government action | -0.01 [-0.12, 0.10] | 186.19 | Extremely strong ●●●●● | Consistent in terms of direction and magnitude of the effect as well as the Bayes factor |
| **H5b:** expectations about others’ government support | 2.36% | .009 |  | Slightly—although not meaningfully—larger and now significant effect |
| **RQ2:** group efficacy beliefs | -0.05  [-0.16, 0.06] | 134.44 | Extremely strong ●●●●● | Consistent in terms of direction and magnitude of the effect as well as the Bayes factor |

*Note.*CrI = credible interval.Insufficient evidence: ○○○○○; weak evidence: ●○○○○; moderate evidence: ●●○○○; strong evidence: ●●●○○; very strong evidence: ●●●●○; extremely strong evidence:●●●●●. Blue indicates evidence in favor of the tested hypothesis or research question; red indicates evidence against it.

# Supplement D

**Deviations from the Preregistration**

|  |  |  |
| --- | --- | --- |
| **Section** | **Preregistered** | **Deviation and Reason** |
| **Introduction:**  **Hypotheses numeration** | Effects of the intervention on:  H3a: expectations about others’ willingness to make lifestyle changes  H3b: own willingness to make lifestyle changes  H4a: expectations about others’ support for government action  H4b: own support for government action  H5: willingness to discuss climate change  H6c: moderation by national identification on group efficacy beliefs | We changed the numeration of the hypotheses as follows:  H3: willingness to discuss climate change (previously H5)  H4a: own willingness to make lifestyle changes (previously H3b)  H4b: expectations about others’ willingness to make lifestyle changes (previously H3a)  H5a: own support for government action (previously H4b)  H5b: expectations about others’ support for government action (previously H4a)  RQ3: moderation by national identification on group efficacy beliefs (previously H6c; since the main effect of the intervention on group efficacy is a research question as well (RQ2), we adapted H6c to RQ3). |
| **Methods:**  **Power simulations** | We ran a priori power analyses using country-level one-sample *t*-tests and country-level regression analyses. | As we planned to use frequentist quasibinomial regressions for the final analyses (instead of *t*-tests in the preregistration) to better model the 0-100% data, we reran the power simulations with quasibinomial regressions. |
| **Methods: Attention check** | We preregistered that we would check participants’ attention with one item, before participants are presented with the control/intervention message: “Please select the option ‘neutral’ and proceed to the following question.” with a response scale from 1 *strongly disagree*, 3 *neutral*, and 5 *strongly agree*. | We decided to include the attention check at the end of the survey to not influence participants’ responses. Based on the panel provider’s request, we changed the attention check to: “With this question, we would like to ensure that participants pay attention. Please select the option ‘Red’ from the list below.” The list included the options *Blue*, *Red*, *Yellow*, *Green*, and *White*. |
| **Methods: Comprehension check** | We preregistered that we would check participants’ comprehension with the following item: “Comprehension will be checked using one item at the end of the survey: Which of these messages have you seen previously in this survey?” | Based on the panel provider’s request, we needed to drop the comprehension check, as it was deemed too difficult for participants. Thus, we also dropped the inclusion criteria of ‘passed comprehension check’. |
| **Methods: Items** | We preregistered that we would assess discussing biodiversity loss, using one item: “How often do you discuss biodiversity loss with others?” Response options are: *often*, *occasionally*, *rarely*, and *never*. | As some participants took longer than 10 min during the pretesting, we decided to drop some of the items from the survey, including the willingness to express one’s opinion on biodiversity loss. Therefore, the randomization (preregistered in Table 4) was not applicable anymore, and we had four instead of eight randomizations: (1) CC own, CC other, BL own, BL other; (2) CC other, CC own, BL other, BL own; (3) BL own, BL other, CC own, CC other; and (4) BL other, BL own, CC other, CC own. |
| **Methods: Control and intervention message** | We had preregistered the following control message:  “Previously, you estimated that [x] out of 100 [NATIONALITY] believe that the climate is changing, and human activity is partly ([x]) or mainly ([x]) responsible.” | We changed “[x] out of 100” to “[x]%” as participants’ in the pretest deemed this more accurate and comprehensible.  The same changes applied to the intervention message. |
| **Methods:**  **Own willingness to make lifestyle changes and support for government action** | We had preregistered the following wording of the two outcomes:  “Consider what [NATIONALITY] believe about climate change. How much, if anything, would you be willing to change about how you live and work to help reduce the effects of climate change?” and  “Consider what [NATIONALITY] believe about climate change. Do you think climate change should be a very high, high, medium, or low priority for the government of [COUNTRY]?” | As participants during the pretesting were confused about considering others’ opinion for this question, we rephrased the items as follows:  “How much, if anything, would you be willing to change about how you live and work to help reduce the effects of climate change?”  “Do you think climate change should be a very high, high, medium, or low priority for the government of [country]?” |
| **Methods:**  **Group efficacy beliefs** | We had preregistered that we would use three items by van Zomeren et al. (2010). | We selected one of the three items, based on participants’ feedback during the pretesting that the items were redundant and thus confusing which was also confirmed by the high reliability (α = 94; van Zomeren et al., 2010).  Consequently, we needed to deviate from the analysis plan to conduct reliability analyses and average across all items. |
| **Methods:**  **Age** | We had preregistered that we would assess age using two items, one to control for in the analyses and one for the quotas:   1. What year were you born? 2. How old are you? 18-29 years, 30-39 years, 40-49 years, 50-59 years, 60 years or older | We assessed age with one item as a control variable:  “How old are you?” Participants could then select their age (in years). For the quota count, we used embedded data that categorized the response into one of five age groups (18-29 years, 30-39 years, 40-49 years, 50-59 years, 60 years or older). |
| **Analysis:**  **Bot exclusions** | ­­— | We added bot detection and excluded responses which likely were provided by bots (reCAPTCHA < .50 as recommended by [Qualtrics](https://www.qualtrics.com/support/de/survey-platform/survey-module/survey-checker/fraud-detection/?rid=langMatch&prevsite=en&newsite=de&geo=AT&geomatch=)) from the analyses. These exclusions are unlikely to change the results, as only 16 responses were excluded. |
| **Analysis: Hypothesis 1a-d** | We had preregistered that we would conduct Bayesian multi-level Gaussian regressions with participants at level 1 and countries at level 2. | We conducted Bayesian multi-level zero-one inflated regression analyses with the four outcomes (i.e., estimated percentage of people who (a) believe in mainly human-caused climate change, (b) believe in partly human-caused climate change, (c) do not believe in human-caused climate change, and (d) do not believe in climate change). We used this strategy instead of the preregistered analysis plan, as posterior predictive checks of both Gaussian and skew-normal models indicated that the actual data are not accurately represented by the model. |
| **Analysis: Hypothesis 1a-d** | — | We calculated sampling weights using automated raking and reweighted the existing cross-quota samples (age and sex) based on the distribution of climate change beliefs in the YouGov survey to ensure adequate representation of all belief groups. |
| **Analysis: Hypothesis 1a-d** | — | To incorporate sampling uncertainty into the actual percentages of beliefs from the YouGov survey, we compared the perceived percentages against a region of practical equivalence (ROPE), defined as the actual percentage from the YouGov survey ± the margins of error based on 95% credible intervals. |
| **Analysis: Hypothesis 2a-d** | We preregistered that we would test Hypothesis 2a-d:  “We, therefore, expect that trend skeptics overestimate the number of trend skeptics more than individuals with other climate change beliefs (i.e., ‘happening but not human-caused’, ‘don’t know’, ‘happening and partly human-caused’, ‘happening and mainly human-caused’; Hypothesis 2a) do.  Attribution skeptics will overestimate the number of attribution skeptics more than individuals with other climate change beliefs (i.e., ‘not happening’, ‘don’t know’, ‘happening and partly human-caused’, ‘happening and mainly human-caused’; Hypothesis 2b) do.  Those who believe that climate change is partly human-caused will underestimate the size of this group less than individuals with other climate change beliefs (i.e., ‘not happening’, ‘happening but not human-caused’, ‘don’t know’, ‘happening and mainly human-caused’; Hypothesis 2c) do.  Those who believe that climate change is mainly human-caused will underestimate the size of this group less than individuals with other climate change beliefs (i.e., ‘not happening’, ‘happening but not human-caused’, ‘don’t know’, ‘happening and partly human-caused’; Hypothesis 2d) do.” | Due toan unexpectedly low number of climate change non-believers in our samples, we could not test these hypotheses. |
| **Analysis: Hypothesis 6a and b, Research Question 3** | We had preregistered that we would test whether national identification moderates the effectiveness of the intervention. | We did not test any hypotheses or research questions about national identification due to very high national identification scores and low variance in our samples. |
| **Analysis:**  **Hypothesis testing** | We had preregistered that we would use one-sided hypothesis tests for all outcomes except group efficacy beliefs. | Since descriptive statistics indicated no differences between the intervention and control condition on any of the outcomes except willingness to express one’s opinion on climate change, we used two-sided hypothesis tests for the five outcomes and a one-sided test for willingness to express one’s opinion. |
| **Exploratory Analyses** | We had preregistered that we would conduct exploratory analyses regarding the pluralistic ignorance effect for biodiversity loss. | These analyses will be reported in a separate manuscript. |

# Supplement E

**Cultural Adaptations of the Translations per Country**

|  |  |  |
| --- | --- | --- |
| **Country** | **Item** | **Adaptation** |
| Brazil |  | None. |
| Canada | Own climate change beliefs | “In general, which of the following statements, if any, best describes your view?” is not really feasible in French. Therefore, we removed "if any" from the sentence. |
| China | Own climate change beliefs    Discuss, own changes, own support, efficacy | in **your view** 您个人的想法 (meaning your **individual** thought). We changed this to improve the flow of the sentence, emphasize it is “your” view, and be more consistent with the others’ CC question. The original English term (climate change) was added in parentheses.  do **you** think **您个人**认为 (meaning **you, on your own**, think). This is also to emphasize it is “your” view/thought.  For all questions containing “you”, a formal “you” (您) was used in Chinese. |
| Germany |  | For all questions containing “you”, a formal “you” (Sie) was used in German. |
| India | Own and others’ climate change beliefs | “The climate is changing and human activity is partly responsible, together with other factors.” We used “reasons” instead of “factors” in Hindi. |
| Indonesia |  | None. |
| Italy | Embedded data  Others’ climate change beliefs    Others’ climate change beliefs, expectations change, and government support | A new embedded field (*Nationality\_Italian*) that corresponds to *Italian* (singular, just in the masculine form that is the general one used in this type of question) was created since in Italian, we would say “*Are you an Italian citizen*?” instead of “Are you a citizen of Italy?”.  To make the instructions clearer, the last sentence (*such that they sum up to 100%*) has been slightly modified as follows: “*in modo tale che Il risultato della loro somma sia 100%”*.  In English, it would be similar to: *such that the result of their sums will be 100%.*  The translated versions of the questions seemed very complicated in Italian and we modified the questions to improve readability: *"Secondo te, quale percentuale di ${e://Field/Nationality\_plural} sarebbe ... / pensa che ...".*  *In English, this would be: According to you / In your opinion, What percentage of ${e://Field/Nationality\_plural}, would be ... / think ...?* |
| Japan | National identification | In Japanese, there is no equivalent for “to identify”, and we used 認識している (= to recognize) instead in the Japanese version. |
| Mexico | Own lifestyle changes | “How much, if anything, would you be willing to change about how…” As the direct translation was not comprehensible in Spanish, we instead used “How willing would you be to change the way you …” |
| Poland | Own climate change beliefs  Expectations change and government support, efficacy  Expectations change  Efficacy  Political orientation | “In general, which of the following statements, if any, best describes your view?” As using the singular of the word ‘view’ does not work in Polish, we used ‘views’ (plural) instead to keep the same meaning.  We had to add a verb to this sentence: “For the following question”, since it would not be feasible if translated directly. The closest translation of the Polish version would be: “Replying for the following question [...]”.  We changed “how they live and work” to a sentence that would be directly translated to “their life and work”. The original was not feasible in Polish.  We have slightly modified one answer category, from “very much” to “a very high extent” in Polish because “very much” does not fit here in Polish.  The term “political orientation” (“orientacja polityczna”) is rarely used in spoken language, so we decided to change it into “political views” to make it easier to understand. The meaning is identical. |
| Thailand |  | None. |

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1. The minimum time for careful completion was 5 min during pilot testing with participants recruited from our personal networks. As participants on data collection panels regularly take part in surveys and are thus often faster than average people, we opted for 3 min as a slightly less conservative threshold for speeding. [↑](#footnote-ref-1)
2. For exploratory purposes, we also assessed own beliefs about biodiversity loss and perceptions of others’ beliefs about biodiversity loss. The order of the climate change or biodiversity loss block was counterbalanced, such that half of the participants per country first completed the block about climate change, whereas the other half first completed the block about biodiversity loss. These results are beyond the scope of the current paper and will be presented elsewhere. [↑](#footnote-ref-2)