Addressing Climate Change with Behavioral Science: A Global Intervention Tournament in 63 Countries

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Abstract

Effectively reducing climate change requires dramatic, global behavior change. Yet it is unclear which strategies are most likely to motivate people to change their climate beliefs and behaviors. Here, we tested 11 expert-crowdsourced interventions on four climate mitigation outcomes: beliefs, policy support, information sharing intention, and an effortful tree-planting behavioral task. Across 59,440 participants from 63 countries, the interventions' effectiveness was small, largely limited to non-climate-skeptics, and differed across outcomes: Beliefs were strengthened most by decreasing psychological distance (by 2.3%), policy support by writing a letter to a future generation member (2.6%), information sharing by negative emotion induction (12.1%), and no intervention increased the more effortful behavior–several interventions even reduced tree planting. Finally, the effects of each intervention differed depending on people's initial climate beliefs. These findings suggest that the impact of behavioral climate interventions varies across audiences and target behaviors.

One sentence summary

Climate interventions increase beliefs, policy support, and willingness to share information, but not higher effort action.

Keywords

Climate interventions; megastudy; climate change; behavior change; international research

Introduction

The climate crisis is one of humanity's most consequential and challenging problems (*1*). Successfully rising to the challenge depends on both "top-down" structural changes (e.g., regulation, investment) as well as "bottom-up" changes (e.g., individuals' and collectives' beliefs and behaviors). These bottom-up processes require wide-spread belief in climate change, support for climate change policy, and willingness to engage in climate action (*2-4*). The behavioral sciences have been seen as a crucial component in promoting bottom-up change, through the development of large-scale interventions that can shift public opinion and enable and support top-down governmental climate policies (*5-7*). Yet it is unclear which strategies are most likely to motivate people to change their climate change beliefs and climate mitigation behaviors. Here, we assess the effectiveness of expert-crowdsourced, theoretically-derived interventions at promoting a range of climate change mitigation behaviors in a large and diverse global sample.

A growing body of research across the behavioral sciences has been investigating intervention strategies aimed at boosting sustainable intentions and behaviors such as recycling, public transportation use, and household energy saving (*3, 8, 9*). For instance, communications aimed at reducing the psychological distance of climate change, by making it feel more geographically, socially, and temporally close, were effective at increasing climate concern, and amplifying self-reported intentions to engage in mitigating behaviors, such as reducing energy consumption (*10*). Similarly, normative appeals that include an invitation to work together and "join in" were found effective at influencing behaviors such as charitable giving (*11*). These are only two examples in a growing list of behavioral interventions designed to mitigate climate change. As such, there are numerous competing theories in the behavioral sciences about how to stimulate climate change beliefs and pro-environmental behaviors.

While many of these theories–and their corresponding interventions–are promising, they have been tested independently with different samples, and on separate outcomes, making it impossible to directly compare their effectiveness. Additionally, assessing interventions on a single outcome renders it difficult to understand their effects on multiple facets of climate mitigation, which are all necessary to significantly reduce climate change (e.g., support for climate mitigation policy and sustainable behavior). These limitations are a major barrier to resolving theoretical debates within the scientific community (*12, 13*) and to translating scientific findings into impactful policies (*14, 15*). Moreover, traditional attempts to compare interventions (e.g., meta-analyses) (*16*)) are limited by differences in experimental protocols, outcome variables, samples, and operationalizations (*17, 18, 19*). These differences hinder evaluations of the relative effectiveness of different theories and interventions (*15*). To address these concerns, we used the *megastudy* approach – an experimental paradigm similar to a randomized controlled trial, but designed to evaluate the efficacy of *many* interventions on several outcome variables, in the same large-scale experiment (*18*). This provides a rigorous direct comparison of competing approaches to climate change mitigation.

Another challenge is that most prior work across the behavioral sciences (including the megastudy approach) has been mainly conducted on Western, Educated samples from

Industrialized, Rich, and Developed countries (i.e., WEIRD) (*20*)). Results from such samples may not generalize to other nations, restricting the ability to apply findings beyond WEIRD populations. This is a particular problem for a topic like climate change where the social and political dynamics, and exposure to the impacts of climate change, vary across countries (*21, 22*). While wealthier nations are disproportionately responsible for causing climate change (*23*), it is still important to understand which interventions work across a diversity of cultures since the most effective mitigation strategies will likely require global cooperation. Accordingly, we leveraged the *many labs* approach, in which the same study is being conducted by many research labs around the world, aggregating the results in the same international dataset (*17, 24*).

In this global megastudy, we crowdsourced interventions previously found to stimulate climate mitigation, from behavioral science experts (Figure S5). We used a crowdsourcing approach to determine which interventions to test, given recent evidence that crowdsourcing can improve the quality of scientific investigations by promoting ideation, inclusiveness, transparency, rigor, and reliability (*25*). This resulted in the identification of 11 behavioral interventions based on competing theoretical frameworks in the behavioral sciences (Fig. 1).

Intervention	Theoretical framework	Description
Dynamic Social Norms	Sparkman & Walton, 2017	Informs participants of how country-level norms are changing and "more and more people are becoming concerned about climate change", suggesting that people should take action.
Work Together Norm	Howe, Carr, & Walton, 2021	Combines referencing a social norm (i.e., "a majority of people are taking steps to reduce their carbon footprint") with an invitation to "join in" and work together with fellow citizens toward this common goal.
Effective Collective Action	Goldenberg et al., 2018; Lizzio-Wilson et al., 2021	Features examples of successful collective action that have had meaningful effects on climate policies (e.g., protests) or have solved past global issues (e.g., the restoration of the ozone layer).
Psychological Distance	Jones, Hine, & Marks, 2017	Frames climate change as a proximal risk by using examples of recent natural disasters caused by climate change in each participants' nation and prompts them to write about the climate impacts on their community.
System Justification	Feygina, Jost, & Goldsmith, 2010	Frames climate change as threatening to the way of life to each participant's nation, and makes an appeal to climate action, as the patriotic response.
Future-Self Continuity	Hershfield, Cohen, & Thompson, 2012	Emphasizes the future self-continuity by asking each participant to project themselves into the future and write a letter addressed to themselves in the present, describing the actions they would have wanted to take regarding climate change.
Negative Emotions	Chapman, Lickel, & Markowitz, 2017	Exposes participants to ecologically valid scientific facts regarding the impacts of climate change framed in a 'doom and gloom' style of messaging that were drawn from different real-world news and media sources.
Pluralistic Ignorance	Geiger & Swim, 2016	Presents real public opinion data collected by the United Nations that shows what percentage of people in each participant's country agree that climate change is a global emergency.
Letter to Future Generation	Shrum, 2021; Wickersham, Zaval, Pachana, & Smyer, 2020	Emphasizes how one's current actions impact future generations by asking participants to write a letter to a socially close child who will read it in 25 years when they are an adult, describing current actions towards ensuring a habitable planet.
Binding Moral Foundations	Wolsko, Ariceaga, & Seiden, 2016	Invokes authority (e.g., "From scientists to experts in the military, there is near universal agreement"), purity (e.g., keep our air, water, and land pure), and ingroup-loyalty (e.g., "it is the American solution") moral foundations.
Scientific Consensus	van der Linden et al., 2015, 2021; Rode et al., 2021	Informs participants that "99% of expert climate scientists agree that the Earth is warming, and climate change is happening, mainly because of human activity".

Figure 1. Interventions, theoretical frameworks, and brief descriptions.

We tested these interventions in a global tournament spanning 63 countries, on four outcome variables, which were also crowdsourced and selected based on their theoretical and practical relevance to climate mitigation. The first outcome on which we assessed each intervention was belief in climate change (4-items; e.g., "*Climate change poses a serious threat to humanity*"). Given that belief is a key antecedent of pro-environmental intentions, behavior, and policy support (*26*), we examined how the interventions would impact these outcomes for different people along the belief continuum ranging from skeptics to true believers.

The second outcome was support for climate change mitigation policy (9-items; e.g., "*I support raising carbon taxes on gas/ fossil fuels/coal*"). Given that successful climate mitigation requires large-scale policy reform (*1*), and the public's support for climate policies is the top predictor of policy adoption (*27*), this outcome variable reflects the importance of impactful systemic change, rather than private mitigation efforts based on individual decision-making (*28-30*). Indeed, recent work argues that individual-level behaviors should be targeted alongside structural changes (*31*), especially since framing climate change as an individual level problem can backfire, leading to feelings of helplessness and concerns about free-riding (*32, 33*).

To target more ecologically valid behavior and climate activism (*34*), the third outcome was willingness to share climate mitigation information on social media (i.e., "*Did you know that removing meat and dairy for only two out of three meals per day could decrease food-related carbon emissions by 60%?*"). While this behavior is relatively low-effort, recent work suggests climate information sharing with one's community as an essential step in addressing the climate crisis (*35*).

Finally, given the large gap between self-reported measures and objective pro-environmental behavior (*36*), the fourth outcome we targeted was a more effortful behavior of contributing to a real tree-planting initiative by engaging in a cognitively demanding task (i.e., a modified version of the Work for Environmental Protection Task or WEPT; *37*). The WEPT is a multi-trial, web-based procedure in which participants choose to exert voluntary effort screening stimuli for specific numerical combinations (i.e., an even first digit and odd second digit) in exchange for donations to a tree-planting environmental organization. Thus, they had the opportunity to produce actual environmental benefits, at actual behavioral costs, mimicking classic sustainable-behavior tradeoffs (*38-40*).

Participants (N = 59,440, from 63 counties; Table 1) were mostly recruited through online data collection platforms (80.8%) or via convenience/snowball sampling (19.1%; Fig 5; Table 1). They were randomly assigned to one of 11 experimental interventions (Fig. 1), or a no-intervention control condition in which they read a passage from a literary text. Then, in a randomized order, participants indicated their climate beliefs, climate policy support, and willingness to share climate-related information on social media. Finally, participants were able to opt into completing up to 8 pages of a tree-planting task, each completed page resulting in the real planting of a tree through a donation to The Eden Reforestation Project. As a result of participants' behavior, our team actually planted 333,333 trees. Assuming that the average fully-grown tree absorbs between 10 and 40 kg of carbon dioxide per year, in 5-10 years when all trees are fully grown, the efforts from this project will result in approximately 9,999,990 kg of carbon dioxide sequestered per year which is the equivalent amount of carbon dioxide used to produce energy for 1,260 US homes.

Results

1. Main effects of intervention

First, we examined the effect of each intervention on each of the four outcomes, estimated using a series of Bayesian regressions (see Methods). As the goal of this study is to estimate the relative effectiveness of treatments, in contrast to establishing non-null effects or differences, Bayesian estimation is preferable to classical Null Hypothesis Significance Testing. Bayesian techniques produce posterior distributions for parameters (here, treatment effects) that characterizes their magnitude and associated uncertainty. We summarize this distribution in the main text using a point estimate corresponding to the mean, and a 94% credible region, which differs from a confidence interval in that it indicates a region with a 94% chance of containing the unobserved parameter value (*41*). Moreover, we also conducted similar frequentist analyses (hierarchical mixed models) and found converging results (see Supplement for details).

We began by assessing the main intervention effects on each outcome. For belief in climate change (measured on a scale from 0 to 100), the top-performing intervention, decreasing psychological distance, increased beliefs by an absolute effect size of 2.3% [1.6, 2.9] (94% Credible Region) compared to the control condition. Consistent with prior work (*10*), some interventions slightly increased beliefs. However, other interventions had near-zero effect, failing to replicate prior research (*11*) (Fig. 2A).

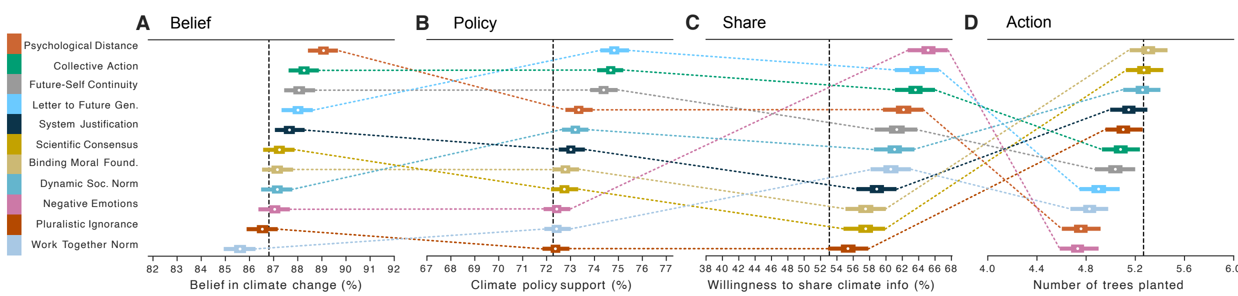

Fig 2. Average effects (i.e., posterior estimates using Bayesian regressions) by intervention for each outcome. Dots indicate the mean, with error bars indicating the 94% credible region (C.R.). Thicker error bars indicate the interquartile range (IQR). Vertical lines indicate control average. A) Belief, B) Support for Policy, C) Willingness to share climate-change information on social media, D) Number of trees planted in the WEPT. Estimates reported in Tables S1-S4.

For climate policy support (measured on a scale from 0 to 100), the intervention with the largest average effect was writing a letter to a member of the future generation, which increased policy support by 2.6% [2.0, 3.2]. Similar to belief, all interventions produced either more policy support or no discernible differences from the control condition (Fig. 2B).

For willingness to share climate change information on social media (measured as a binary choice), all interventions generally increased intentions to share. The largest gains were exhibited in the negative emotion induction condition, which led to 12.1% [9.8, 14.6] more sharing compared to the control condition (Fig. 2C).

For the number of pages completed on the WEPT tree planting task (from 0 to 8), no intervention was better than the control condition, and some interventions (i.e., decreasing psychological distance, inducing negative emotions, work-together normative appeals, and writing a letter to a future generation member) appeared to reduce tree-planting (Fig. 2D). These results held regardless of the operationalization of a tree planted as participants' confirmation that they wanted to complete another WEPT page, or their accuracy in the task (Table S24).

The interventions that produced negative effects on the WEPT were also those that took the most time to complete (Supplement Analyses). Assuming participants have a limited budget of time for completing surveys, and given the tree planting task requires time, it is unsurprising we observed a tradeoff between the time spent on the intervention and on the outcome task. Therefore, in an exploratory analysis (Tables S22, S23) we assessed the effects of the interventions when adjusting for the time spent on each intervention. While we still observed the negative effects of some interventions on tree planting, we now also observed positive effects of five interventions. That is, when controlling for intervention length, Binding Moral Foundations, Scientific Consensus, Dynamic Norms, Pluralistic Ignorance, and System Justification all increased the number of trees planted compared to the control condition. Thus, in the absence of time constraints, such interventions might increase pro-environmental behavior. However, the degree to which these findings actually generalize to pro-environmental behaviors that do not hinge on time (e.g., donations) should be assessed in future studies.

For further assessing the average effects of each intervention on each outcome within any subsample of interest varying along demographics such as nationality, political ideology, age, gender, education, or income level, we provide an easy to use and disseminate webtool: https://climate-interventions.shinyapps.io/climate-interventions/.

2. Heterogeneous intervention effects along initial belief continuum

We found a high level of belief in climate change (i.e., 85.7% [85.2, 86.2], an estimate computed using the ratings of belief in the control participants and estimated pre-intervention levels of belief from all other participants). This could raise two potential concerns when evaluating the main effects of the interventions mentioned above: On the one hand, at this high level of belief, participants may be particularly receptive to interventions. As a result, average effects may tend to overestimate the effectiveness of interventions in applied contexts where the aim is to increase belief or policy support in skeptical participants that do not already believe in climate change. On the other hand, as our outcomes are bounded, these high levels of belief may lead to ceiling effects in the estimation of the average effects, which may *undervalue* the true effectiveness of the interventions. To address this concern, we conducted an additional analysis where we modeled heterogeneous effects as a function of unobserved pre-intervention belief (see Methods, SI). This analysis allowed us to visualize how effective interventions were across the continuum from climate change skeptics (i.e., those with initial beliefs less than 35%) to true believers (i.e., those with initial beliefs higher than 65%; Fig 3).

For the impact of interventions on belief (Fig 3A), we found clear indications of ceiling effects with many interventions being maximally impactful among uncertain participants, even those with *low to moderate levels of initial belief*. Even in participants with low levels of pre-existing climate change belief (i.e., less than 35%), interventions like reducing psychological distance, future self continuity, and effective collective action are all viable ways to increase belief in climate change.

For policy support, a different pattern emerged. Interventions like writing a letter to a member of the future generation, collective action efficacy, future-self continuity, and decreasing psychological distance all increased support for climate policy (Fig 3B). Those same interventions appear to function well on individuals with modest to high levels of initial climate change belief (i.e., at approximately 35-90%; Fig 3B). However, they were relatively ineffectual amongst those that were low in initial belief (i.e., climate skeptics). The main exception is in writing a letter to a member of the future generation intervention, which worked across nearly the entire spectrum of initial belief. Additionally, for those that were very low to moderate (i.e., 0-65%) on initial belief, the negative emotion intervention appeared to backfire, reducing support for climate change policies. Similar to belief, the work together normative appeal also slightly backfired in participants with moderate levels of initial belief.

Regarding social media sharing, nearly all interventions (i.e., 9 out of 11) increased willingness to share even at moderate levels of initial belief (i.e., those greater than approximately 35-60%). Moreover, the increase in willingness to share by inducing negative emotions extended into individuals who generally do not believe in climate change. Finally, the work-together normative appeal intervention backfired amongst those who are very low on initial belief (i.e., approximately 0-15%), reducing their willingness to share information on social media by up to 12%.

Finally, for the tree planting task, more than half of the interventions decreased the number of pages completed on the WEPT across all levels of initial belief (Fig 3D).

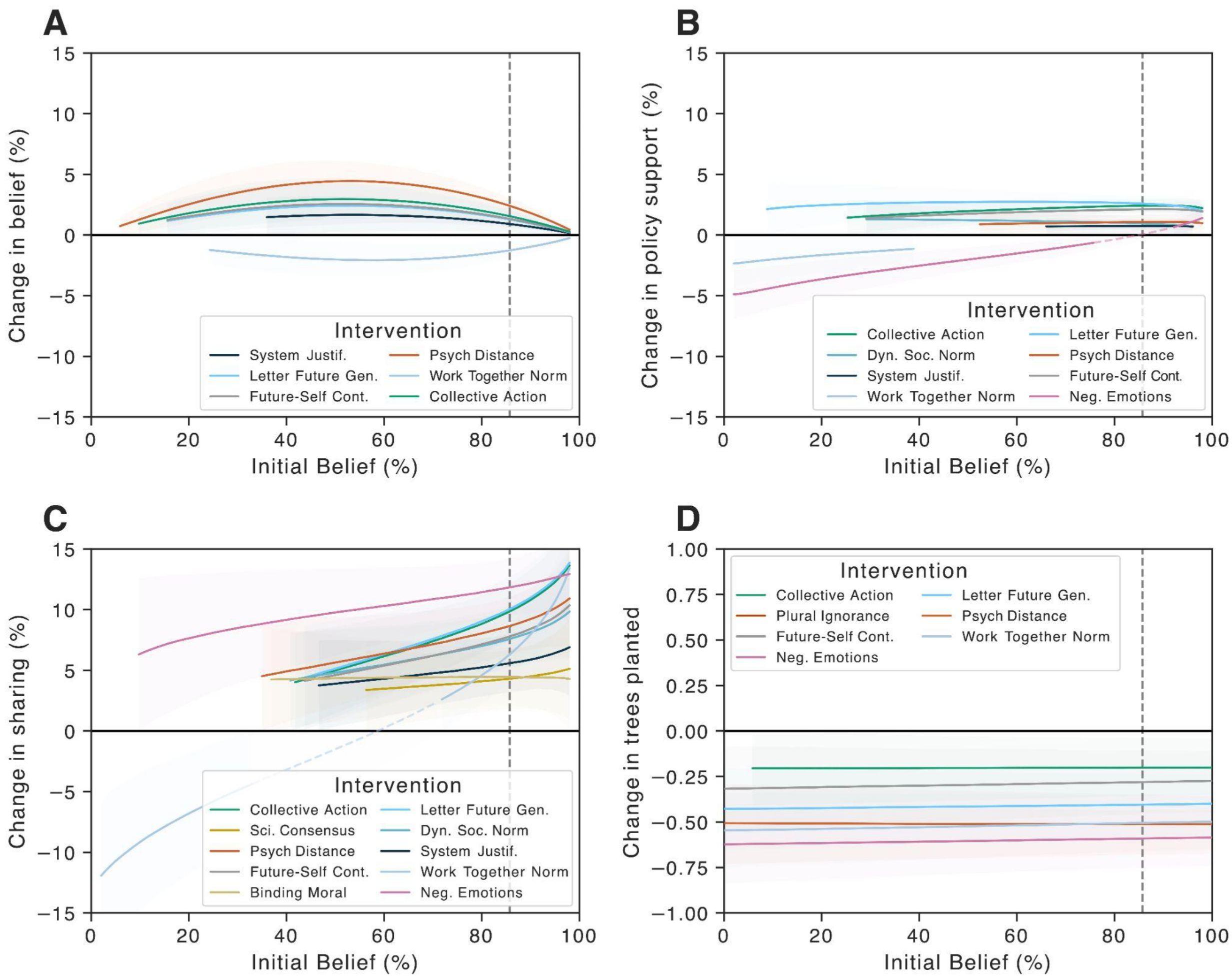

Fig 3. Marginal effects (as the difference between interventions and control) as a function of estimated pre-intervention belief in climate change. Lines indicate the average effect size, with shaded regions indicating the 94% credible region (C.R.). For visual clarity, regions in which the 94% C.R. overlap zero are omitted from the figure. Where interventions have positive and negative effects that meet these criteria, a dashed line is used to connect these regions. The dashed vertical line indicates average belief, where effects in Figure 1 are estimated. A) Climate change Belief, B) Policy Support, C) Sharing information on social media, D) Trees planted via the WEPT.

3. Country-level main effects

Finally, we examined the country-level main effects for each of our key outcome variables. We found that average belief in climate change, across all countries surveyed, was high (85.7% [85.2, 86.2]. This includes both ratings of belief in the control participants and estimated pre-intervention levels of belief from all other participants). Importantly, there was very little variation between countries (Fig 4A & Fig S4A; Table S5) indicating a clear majority belief in climate change. Similar patterns were observed for policy support (Fig. 4B), with all countries indicating clear majority support for a variety of climate change policies (72.2% [71.6, 72.8]). These results suggest that there is clear and consistent global consensus regarding the dangers posed by climate change and the importance of enacting climate change mitigation.

Other outcome variables exhibited larger variation across countries. Willingness to share climate–change related information on social media was more modest (56.9 [56.4,57.5]) and variable, ranging from a low in Latvia of 17.6% [14.3,21.4] to a high of 93.3% [90.4, 95.7] in Kenya (Fig 4C). These results suggest that observations of climate-change discussion online may not accurately reflect global sentiments about the reality of climate change, but rather different local norms.

Finally, half of all participants (50.7% of total sample; 53.1% of control condition sample) completed all eight pages of the WEPT, earning the maximum number of trees possible, with an overall average of 5.2 [5.1, 5.3] pages completed (Fig. 4D).

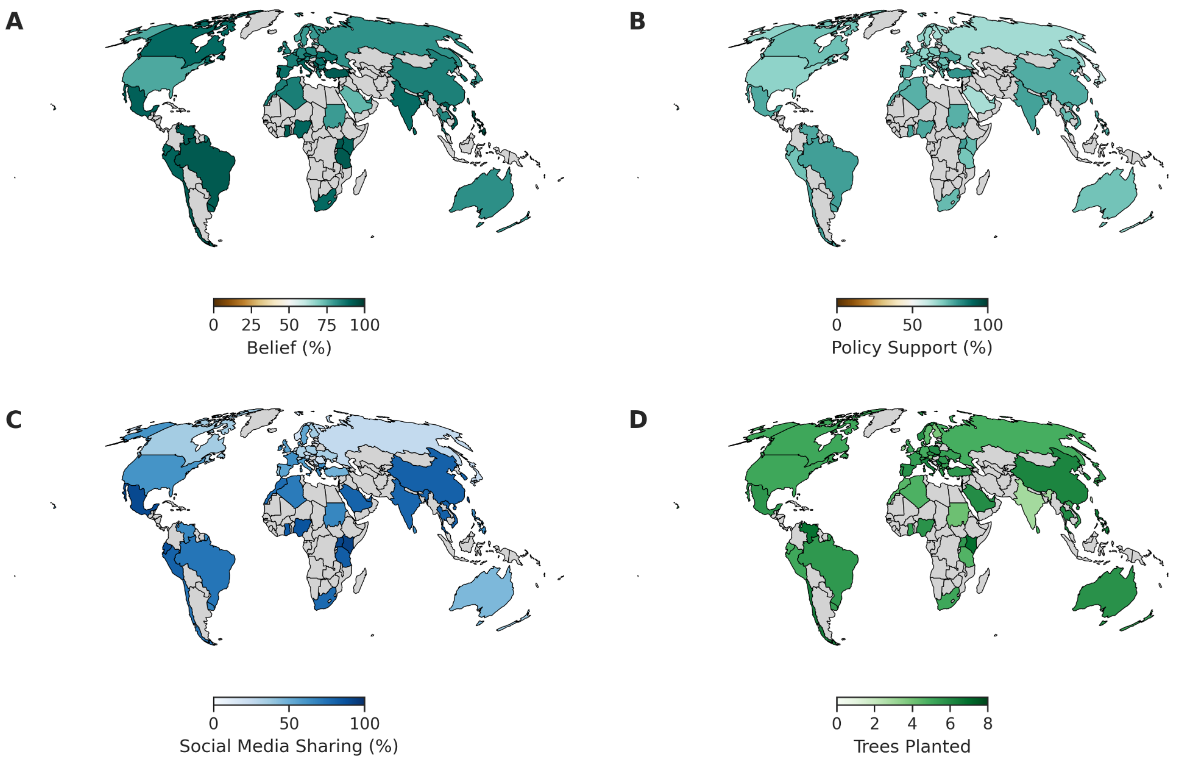

Fig 4. Country-level means of each outcome variable. Countries without available data are shown in gray. Statistics shown in Tables S5-S8. A) Climate change Belief, B) Policy Support, C) Sharing information on social media, D) Trees planted via the WEPT.

Discussion

In a global megastudy conducted on a sample of 59,440 people from 63 countries, we empirically assessed the relative effectiveness of 11 expert-crowdsourced, theoretically-derived behavioral interventions at stimulating climate mitigation beliefs and behaviors (i.e., climate change beliefs, policy support, willingness to share information, and tree planting contributions). We found that different interventions tended to have small global effects, which varied across outcomes and largely impacted non-skeptics, emphasizing the importance of examining the impact of climate interventions on a range of outcomes before drawing conclusions regarding their overarching relative efficacy. These findings suggest that the impact of behavioral climate interventions varies across audiences' characteristics and target behaviors.

Here, climate change beliefs were strengthened most by decreasing the psychological distance of climate change. Support for climate change mitigation policy was increased most by writing a letter to be read in the future by a socially close child, describing one's current climate change mitigation actions. Willingness to share climate change information on social media was increased most by inducing negative emotions through "doom and gloom" styled messaging about the consequences of climate change. Finally, while half of the tested interventions had no effect on the effortful tree-planting behavior, the other half of the interventions reduced the number of trees participants planted. Beyond revealing the utility of harnessing a multi-outcome approach, these results also highlight the need for tailoring interventions to target outcomes.

Our findings extend prior work and are theoretically informative in several ways. Notably, these findings help reconcile several theoretical debates in the literature. For example, some have argued in favor of employing a "doom-and-gloom" messaging style in climate communications (i.e., induce negative emotions) as a way to stimulate climate mitigation behaviors (*43*). For instance, recent work found that online news consumption is largely driven by the negative content of the news (*44*). However, others have warned that such messaging may have no impact on behavior (*45*), or worse, that it may depress and demoralize the public into inaction (*46*). Here, we found empirical support for both accounts on different outcomes: while negative emotion messaging was highly effective at stimulating climate information sharing intentions (a relatively low-effort behavior), it decreased tree planting efforts. Further, the negative emotion induction intervention appeared to backfire on policy support among participants with low initial climate beliefs. These results suggest that climate scientists should carefully consider the differential effects of the prevalent fear-inducing writing styles on different pro-climate outcomes. Moreover, it suggests that theoretical models need to explain divergent patterns across outcomes.

The results also indicate the impact of the interventions on each outcome depends on peoples' pre-existing belief in climate change, supporting the claim that interventions need to be tailored to the characteristics of their audience (*45, 46*). For belief, the effectiveness of several interventions (e.g., decreasing the psychological distance, and collective action efficacy) was maximized among the uncertain, with lesser effects among believers and skeptics. For policy support, however, interventions were generally only effective among those with high initial levels of belief, with negative emotions backfiring among skeptics. Similarly, the robust increases in willingness to share on social media were largely restricted to people who already believed in climate change—with negative emotions increasing sharing intentions even among skeptics. For the higher effort behavior, however, interventions appeared to uniformly reduce tree planting across all levels of initial belief.

Given the heterogeneity of these results across outcomes, we created a web tool resource (https://climate-interventions.shinyapps.io/climate-interventions/) that can easily and rapidly assess intervention efficacy across each of the four outcomes and across a range of variables, including country, political ideology, gender, age, socioeconomic status, income, and education. While we caution that users must take into account the sample sizes when exploring subsamples of the data, and the fact that they are looking at percentage of change compared to the control condition, this web tool can be used as a rapid and intuitive way to query intervention efficacy within subsamples of interest. For example, for highly educated conservatives in the United States, the top intervention to increase climate policy support was the future-self continuity intervention, increasing support by 18%. This intervention also increased climate beliefs in Russian participants by 9%. The scientific consensus intervention increased climate policy support by 9% in Romania, but decreased it by 5% in Canada. The binding moral foundations intervention increased the number of trees planted by Australians under the age of 40 by 40%, and by Gambians by 35%, but this intervention decreased the number of trees planted by wealthy Japanese participants by 24%. Such results can inform the development of local intervention strategies, which should then be empirically validated. Critically, these results also bolster the message that interventions need to be tailored to the characteristics of the target audience, nationality being an important factor. The accompanying data exploration web tool and the open-source raw dataset, contribute to the data-as-public-good trend emerging in the spirit of open science, thus facilitating the testing of additional hypotheses and advancement of science.

Importantly, in a linked forecasting experiment (*42*), academics (e.g., behavioral scientists) and the general public were asked to predict how each intervention would impact belief, policy support, and the tree-planting behavior in a subset of participants from this study (i.e., those from The United States). While academics were better than the general public at predicting the efficacy of these interventions on beliefs and policy support, when compared to statistical models using simple heuristics like “interventions would have no effect”, no group was able to accurately predict how interventions would impact behavior. These results suggest that our findings here, reflect an important departure from the expectations within the academic community.

There are also several limitations and future directions that should be emphasized. First, the sampling procedures differed between countries (e.g., the U.S., and Israel samples matched the census on age, gender, region, ethnicity; the Norway sample matched on age, gender, ethnicity; etc; Table 1). It should be noted that 73.6% of the entire sample were matched for at least one variable. However, despite these differences, recent work has found that representative samples are not required to obtain generalizable estimates of effect sizes within countries (*47, 48*). Indeed, various analyses have highlighted that convenience samples are adequate for estimating treatment effects (*49, 50*). As such, given that our paper is primarily concerned with the effects of these interventions rather than with estimating levels of opinion within each country, our sampling procedures were appropriate for the analyses and conclusions drawn here. However, while realizing it will be a challenge, we encourage future work to examine these processes using larger, more representative samples from an even broader sample of countries.

Second, we leveraged an online survey-based approach, which means that we were able to capture a limited set of contextual factors that may have influenced our results. This approach was the most effective way to measure and compare intervention efficacy in such a diverse global sample. However, one important and potentially impactful avenue for future research could be to leverage these findings to conduct local field experimentation in targeted samples.

One of the major strengths of our tournament was testing eleven different interventions simultaneously in a large global sample across multiple outcomes. Given the heterogeneity in the effectiveness of the interventions across the outcomes, future work should likewise prioritize testing promising interventions on even more climate-relevant antecedents and outcomes, for a more comprehensive assessment of climate interventions and their underlying theoretical frameworks. One constraint we faced when attempting to test additional theories was the decision to not use deception in our interventions. For example, descriptive or injunctive norm based interventions would have needed to be based on deception to be included in a deployed at this global scale, given the unavailability of the empirical information critical to creating these interventions. We hope the current dataset can provide this information for future research in international contexts. Future work should also investigate additional pro-environmental behaviors, such as investment decisions, activism, advocacy, or civic participation, critical to climate change mitigation.

Future research should also assess the processes behind the negative effects we observed on the tree planting task. Here, we find evidence for a tradeoff between time spent on the intervention and in the behavioral task, but additional processes may also be at play. For instance, the negative effects observed might suggest a negative spillover process, by which increasing some mitigation actions (e.g., policy support, social media sharing, etc.) could have decreased other mitigation actions (e.g., contributing to tree planting). Given that the tree planting task was also the last outcome variable completed by participants in, such a process could be plausible. However, each of the first three outcomes (i.e., climate belief, climate policy support, and information sharing willingness) were positively associated with the last outcome (i.e., WEPT; Fig S2, Tables S13–S15). These positive associations at the study level also held within each of the 12 conditions (Tables S16–S18). That is, the more a participant supported climate policy the more trees they planted, a pattern found in each condition (Table S17). Similarly, participants who were willing to share climate information on social media also planted more trees, again a pattern found within each condition (Table S18). These positive associations are more consistent with a positive spillover.

An alternative explanation for the intervention effects on the tree planting task could be that current behavioral science theories and their corresponding interventions are more effective at targeting conceptual processes compared to more effortful and time-consuming behavioral signatures, especially in such a heterogenous global sample. Yet another explanation could be that interventions that made the negative consequences of climate change more salient (e.g., negative emotions, decreasing of psychological distance, future-self continuity), triggered the perception that individual-level solutions (e.g., planting trees) may be futile in the face of such an insurmountable phenomenon, in line with the learned helplessness hypothesis (*46*). Or perhaps, a combination of these explanations gave rise to the effects observed. Future research is needed to clarify these processes, and identify interventions that increase more effortful climate actions around the world, as well as actions that are more effective solutions to the climate crisis (*30*).

Finally, while in this global study we tested the effects of several theoretically-derived behavioral interventions on people's beliefs and actions in the context of climate change, our findings provide meaningful insights to the broader fields of social and behavioral sciences. For instance, the average global effects of the interventions tested ranged from effectively zero to very small in the conceptual outcomes (beliefs, policy support), and near-zero to negative in the behavioral outcome (tree planting). These findings point to critical limitations in these theories' utility and generalizability beyond the contexts in which they were developed. The most extreme example is the correcting pluralistic ignorance intervention, which had no effect on beliefs, policy support, or willingness to share information on social media, and even reduced tree planting efforts. Indeed, theories are often tested and evaluated mainly on their ability to account for decontextualized patterns of data in laboratory settings, rather than their ability to help solve societal problems (*51*). In response to this limitation, researchers have recently proposed reverting the scientific paradigm to an impact-oriented theoretical and empirical research agenda (*30*).

The small effect sizes we observed in this global sample might also be partly interpreted through the lens of recent work reporting that over 60% of studies in the most prestigious journals in psychology have only focused on 11% of the world's population (*52*). Indeed, in our data collected in the US or other WEIRD nations, the effects of the top interventions on belief and policy support were much stronger than at the global level. The skewed representation in the field may pose another significant obstacle in addressing societal problems that depend on global cooperation and a diversity of solutions for different cultural contexts, as is the case in climate change among numerous others global crises. One promising solution to these generalizability and practicality limitations in the behavioral sciences relies on embracing international collaborative science. Indeed, large global scientific projects can benefit from access to a wider range of populations, but also from a diversity of scientific perspectives. For example, crowdsourcing has been found to improve the quality of scientific investigations by promoting ideation, inclusiveness, transparency, rigor, reliability among other factors (*25*). Thus, crowdsourcing decisions related to the experimental design from experts more widely representative of the global scientific community might increase the impact and generalizability of scientific investigations. For example, the crowdsourcing of the theories tested from our large international team, has led us to include less established interventions, such as "letter to future generation", which ended up being one of the top interventions tested. Future work could also consider extending this crowdsourcing paradigm to include non-experts (e.g., lay audiences), as recent work suggests that there may be unique benefits (e.g., increased interdisciplinarity), sometimes even producing research questions that outperform experts' suggestions (*53*). Finally, combining this "many labs" approach (*24*) with the megastudy approach (*18*), promises to push the limits of conventional scientific practices, and overcome some of the main barriers of science generalization and implementation (*54*).

Overall, we tested the effectiveness of 11 expert-crowdsourced behavioral interventions, at increasing climate awareness and action in 63 countries. Our findings provide theoretical support for many of the tested interventions. However, variation in effectiveness across outcomes, between countries, and along the spectrum of climate beliefs, suggest significant gaps in our current theoretical understanding of climate change behavior. Moreover, the high pre-existing levels of belief and policy support, alongside the small effect sizes observed here, raise critical questions about the practical capacity to facilitate bottom-up change at a global level, suggesting that top-down change might need to be prioritized to achieve the emissions reduction necessary to stay within safe planetary limits for human civilization. Practically, these findings provide critical information to policymakers considering climate solution implementations, streamlining the behavioral sciences' response to the climate crisis.

Materials and Methods

Participants. The data were collected between July 2022 and May 2023. A total of 83,927 completed the study. Of them, 59,440 participants (M_{age}=39.13, SD_{age} =15.76; 50% women, 46% men) from 63 countries (Fig 5; Table 1) who passed the two attention checks (i.e., *Please select the color "purple" from the list below."* and "*To indicate you are reading this paragraph, please type the word sixty in the text box below."*) and correctly completed the WEPT demo, were included in the analyses. Although removing participants who failed these preregistered attention checks risks contributing to a selection bias in the sample (*55*), we *a priori* determined we would screen participants according to these criteria to ensure data quality.

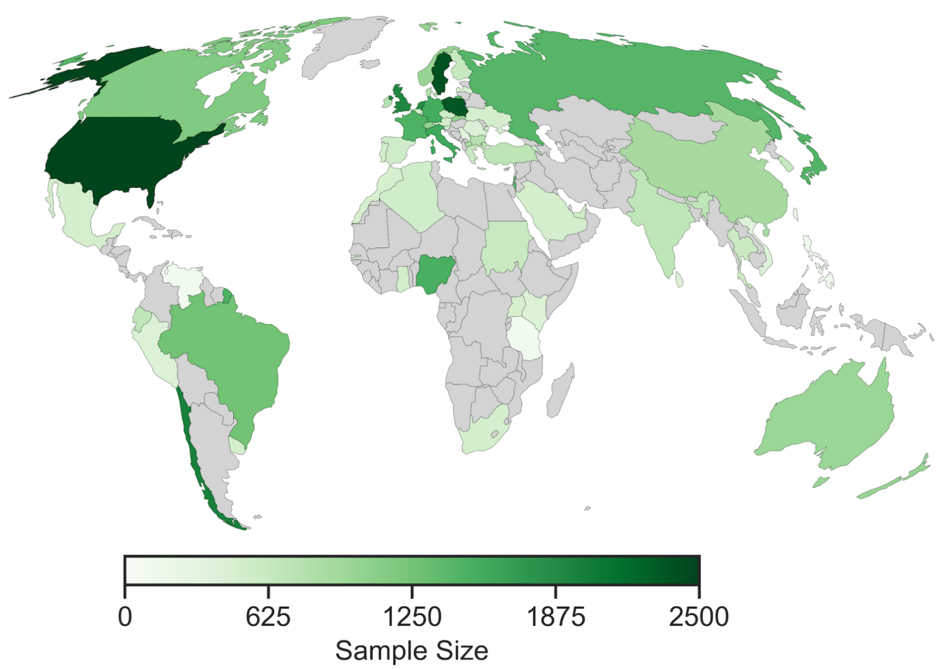

Fig 5. The number of participants in each of the 63 countries represented in the sample (N_{total}=59,440).

Ethics approval was obtained independently by each data collection team from their corresponding Institutional Review Board (IRB). Only datasets submitted along with IRB approval were included in the analysis.

Table 1. Variables on which the samples in each country were matched to the population. Countries in which no demographic variable was census matched are marked as "N/A" in the "Matched Variables" column.

Sample	Matched Variables	N	Sample	Matched Variables	N
Algeria	N/A	528	Philippines	N/A	145
Armenia	N/A	492	Poland_1	Age, Gender, Education	1883
Australia	Gender	979	Poland_2	N/A	463
Austria	Age, Gender	502	Portugal	N/A	499
Belgium_1	Age, Gender	522	Romania	N/A	411
Belgium_2	Age, Gender	512	Russia_1	N/A	718
Brazil	Age, Gender, Education	1261	Russia_2	Region, Ethnicity	395
Bulgaria	Age, Gender	778	Russia_3	N/A	322
Canada_1	N/A	858	Saudi Arabia	N/A	489
Canada_2	Age, Gender	303	Serbia	N/A	337
Chile	Age, Gender, Region, SES	1992	Singapore	N/A	500
China	N/A	896	Slovakia	Age, Gender, Region, Municipality Size	1027
Czechia	N/A	547	Slovenia	Age, Gender	501
Denmark	Age, Gender, Region	792	South Africa	Age, Gender	496
Ecuador	Age, Gender, Region	679	South Korea	Age, Gender	639
Finland	Age, Gender	625	Spain_1	N/A	110
France	Age, Gender	1480	Spain_2	Age, Gender, Region	434
Gambia	N/A	527	Sri Lanka	N/A	413
Germany	Age, Gender, Region	1545	Sudan	Age, Gender	623
Ghana	Age, Gender	522	Sweden	Age, Gender	2393
Greece	Age, Gender	597	Switzerland_1	Age, Gender	512
India	N/A	688	Switzerland_2	Age, Gender	531
Ireland	N/A	753	Taiwan	N/A	206
Israel	Age, Gender, Region, Ethnicity	1384	Tanzania	Age, Gender	104
Italy_1	Age, Gender, Region	591	Thailand	N/A	586
Italy_2	Gender	993	Turkey_1	N/A	359
Japan_1	N/A	653	Turkey_2	Age, Gender	347
Japan_2	Income, Education, Region, Ethnicity	802	Uganda	Age, Gender	476
Kenya	Age, Gender	409	UK_1	N/A	220
Latvia	Income, Education, Ethnicity	485	UK_2	Age, Gender	952
Mexico	Age, Gender	490	UK_3	N/A	234
Morocco	Age, Gender	474	UK_4	Gender	501
Netherlands_1	Age, Gender	854	Ukraine	N/A	496

Netherlands_2	Age, Gender	510	UAE	Broadly representative	554
Netherlands_3	N/A	500	Uruguay	N/A	838
New Zealand	Gender	1005	USA_1	Age, Gender	2360
Nigeria	Age, Gender	1513	USA_2	Age, Gender, Region, Ethnicity	5055
North Macedonia	N/A	878	USA_3	Age, Gender	497
Norway	Age, Gender, Ethnicity	997	Venezuela	N/A	110
Peru	Age, Gender	405	Vietnam	N/A	383

Collaboration Procedure. Following procedures from Van Bavel and colleagues (*24*), the organizational team submitted a call for collaboration (https://manylabsclimate.wordpress.com/call-for-collaboration/) in November 2021 on social media (i.e., Twitter), via personal networks, and by posting on various mailing lists. We asked researchers from around the world to join our project by contributing in one of three ways: (1) collecting data (i.e., >500 responses) from a new country, (2) propose an intervention that becomes included in the final study, and/or (3) fund data collection (i.e., >500 responses) from a new country and support a local team who lacks funding. The collaborators who proposed an intervention were asked to keep in mind time constraints (i.e., each intervention had to take on average at most 5 minutes) and the targeted outcome variables (i.e., climate beliefs, policy support, social media sharing, and tree planting contributions). We received a total of 36 proposed interventions, which were coded by the first authors (who were blinded to the intervention authors). The coding procedure involved screening the proposed interventions for feasibility in an international context, relevance for the dependent variables, and theoretical support from prior work (quantified by previously reported effect sizes). We also aggregated similar interventions and duplicates. Following this procedure, we identified 11 unique and feasible interventions, which we then asked all collaborators to rate on perceived efficacy (practical support) and theoretical value (theoretical support), initially aiming to select the top five interventions. We obtained 188 responses from our collaborators in January 2022 (Fig. S5). Given high support for all interventions, we decided to test all 11 interventions in the main study. We then contacted the collaborators whose interventions had been selected to be included in the main study, to coordinate the intervention implementation and programming on the Qualtrics survey platform (https://www.qualtrics.com/). After obtaining the programmed interventions, we gave our collaborators feedback on their submissions and allowed them time to address our comments. After receiving the revised interventions, we contacted expert researchers who had published theoretical work relevant to each intervention, asking them to critically review each intervention's implementation. For example, Professor John Jost reviewed the System Justification intervention (*57*) and Professor Sander van der Linden reviewed the Scientific Consensus intervention (*58*). This process was iterated for each of the 11 interventions. After receiving critical suggestions from these experts we engaged in another round of revisions. Finally, in an attempt to reduce American-centric researcher biases, we asked all collaborators from around the world for additional feedback on the entire survey, including all interventions, demographics, and independent variables. This process lasted until the end of May 2022, when we started piloting the final version of the study, on a sample of 723 participants (M_{age}=43.6; SD_{age}=15.7; 52% women, 46% men, <2% non-binary), collected in the United States. Using the pilot data, we wrote our analysis scripts and the pre-registration (available here: https://aspredicted.org/blind.php?x=W83_WTL). After the piloting was completed (July 2022), we sent our collaborators the final version of the study in Qualtrics along with an in-depth instructions manual (https://osf.io/ytf89/files/osfstorage/6454f8e3b30b49156cb9dd79/) on how to translate and adapt the study to each country. We also instructed our collaborators to obtain ethics approval from their institutions' review boards before launching data collection. All collaborators were given 10 months (until May 2023) to submit their data.

Experimental design. Participants signing up to complete the study (expected to take 15 minutes to complete) were first asked to read and sign the informed consent. They were then exposed to the first attention check ("*Please select the color "purple" from the list below. We would like to make sure that you are reading these questions carefully.*"), which removed from the experiment any participants choosing an incorrect answer. Then, participants were then given a definition of climate change: "*Climate change is the phenomenon describing the fact that the world's average temperature has been increasing over the past 150 years and will likely be increasing more in the future.*" After reading this definition, participants were randomly assigned to one of 12 conditions: 11 experimental interventions (Fig. 1), or a no-intervention control condition, in a between-subjects design. Participants in the control condition were then exposed to a short, thematically unrelated text from the novel "*Great Expectations*" by Charles Dickens, while participants in the experimental conditions were exposed to an intervention. Then, all participants were directed to the outcome variable phase, in which they rated (in random order) their (1) climate beliefs, (2) climate policy support, (3) willingness to share climate information on social media. Finally, participants were given the chance to contribute to tree planting efforts by completing the WEPT. Then, participants in the control condition were asked to complete an additional set of variables. Finally, all participants were asked to fill out a series of demographic variables, which included another attention check ("*In the previous section you viewed some information about climate change. To indicate you are reading this paragraph, please type the word sixty in the text box below.*"). Of note, participants filled out the entire survey in the primary language of their country of residence.

Outcome variables.

Climate beliefs. Climate beliefs were measured by participants' answer to the question "*How accurate do you think these statements are?*" from 0=*Not at all accurate* to 100=*Extremely accurate*. The four statements were: "*Taking action to fight climate change is necessary to avoid a global catastrophe", "Human activities are causing climate change", "Climate change poses* *a serious threat to humanity",* and *"Climate change is a global emergency".* The Cronbach's alpha measure of internal consistency of this 4-item scale in this dataset was 0.934.

Climate policy support. This dependent variable consisted of participants' level of agreement from 0=*Not at all* to 100=*Very much so*, with the following nine statements: "*I support raising carbon taxes on gas/fossil fuels/coal?*", "*I support significantly expanding infrastructure for public transportation*.", "*I support increasing the number of charging stations for electric vehicles*.", "*I support increasing the use of sustainable energy such as wind and solar energy.*", "*I support increasing taxes on airline companies to offset carbon emissions.*", "*I support protecting forested and land areas.", "I support investing more in green jobs and businesses.", "I support introducing laws to keep waterways and oceans clean.", and "I support increasing taxes on carbon intense foods (for example meat and dairy)*." The Cronbach's alpha measure of internal consistency of this 9-item scale in this dataset was 0.876.

Social media sharing. Participants were first presented with the text, "Did you know that removing meat and dairy for only two out of three meals per day could decrease food-related carbon emissions by 60%? It is an easy way to fight #ClimateChange #ManyLabsClimate${e://Field/cond} source: https://econ.st/3qjvOnn" (where "{e://Field/cond}" was replaced with the condition code for each group). Participants were then asked "*Are you willing to share this information on your social media?*", the answer options being "*Yes, I am willing to share this information", "I am not willing to share this information*", and "*I do not use social media*". Participants who indicated they do not use social media were excluded from this analysis (i.e., a third of the sample). Moreover, participants were asked to indicate the platform (e.g., Facebook, Twitter, Instagram) on which they posted the information.

WEPT Tree planting efforts. To measure an action with a real-world impact performed at an actual cost to participants, we used a modified version of the work for environmental protection task (WEPT) (*37*)). This task is a multi-trial web-based procedure that detects consequential pro-environmental behavior by allowing participants the opportunity of engaging in voluntary cognitive effort (i.e., screen numerical stimuli) in exchange for donations to an environmental organization. This measure has been validated and has been found to correlate with well-established scales for the assessing pro-environmental behavioral intentions (e.g., General Ecological Behavior scale, GEB, *59*) and with direct donation behaviors (e.g., the donation of a part of their payment to an environmental organization; *39*).

Participants were first exposed to a demonstration of the WEPT, in which they were instructed to identify all target numbers for which the first digit is even and the second digit is odd (4 out of 18 numbers were target numbers on the demonstration page). Participants were not allowed to advance the page until they correctly completed the WEPT demonstration. Then, they were told that planting trees is one of the best ways to combat climate change, and that they would have the opportunity to plant up to 8 trees if they chose to engage in additional pages of the item identification task (one tree per page of WEPT completed). These pages contained 60 numbers per page, which participants had to screen for target numbers. Alongside these instructions participants were shown a pictogram of 8 trees, one of which was colored green to mark their progress in the task. Participants were allowed to exit the task at any point with no penalty.

Demographics. Participants were asked to indicate their gender, age, education level, political orientation for economic and social issues, and household income.

Experimental Conditions (Interventions)

Working-Together Norms (submitted by Madalina Vlasceanu and Jay Van Bavel)**.** This intervention was adapted from Howe, Carr, and Walton (*11*) and it combines referencing a social norm with an invitation to work with others toward a common goal. This working-together normative appeal invites people to "*join in*" and "*do it together*," and has been found to increase interest in and actual charitable giving, reduce paper-towel use in public restrooms, and increase interest in reducing personal carbon emissions (*11*). Mediation analyses in prior work also suggested that working-together normative appeals are effective because they foster a feeling in participants that they are working together with others, which can increase motivation while reducing social pressure. Participants in this condition were exposed to a flier adapted from Howe and colleagues (*11*), after which they were asked 15 questions about the flier, serving as manipulation checks that were also meant to reinforce the manipulation (e.g., "*If you are taking steps towards reducing your carbon footprint, to what extent would you feel like you are doing so together with other Americans [or participants' group, adapted for each country]?"* on a scale from 0=*Not at all* to 100=*Extremely*, or "*How strongly do you identify with your fellow Americans [or participants' group, adapted for each country]?*" on a scale from 0=*Not at all* to 100=*Extremely*).

System justification (submitted by Ondrej Buchel, Michael Tyrala, Andrej Findor). This intervention is situated at the intersection of social identity, collective narcissism, and system justification approaches (based on *60*), and consists of framing climate change as uniquely threatening the way of life of participants' nationality (e.g., the *American* way of life). Participants were asked to read a text emphasizing the importance of nature and the environment to one's life (e.g., "*(..) the food you eat, the sports you enjoy, the customs you observe, how you spend your free time, or even how you imagine growing old, all are likely impacted by where you live"*), followed by examples of the effect of climate change on the local environment of participants' nation (e.g., "*(..) we can already see the consequences of climate change in the United States. For example, floods are becoming more and more frequent, putting a quarter of Americans at risk of losing their homes. Similarly, wildfires are becoming more frequent and more intense, threatening millions of Americans.").* The text ends with an appeal to being pro-environmental as a patriotic gesture that will protect one's way of life (e.g., "*Being pro-environmental allows us to protect and preserve the American way of life. It is patriotic to conserve the country's natural resources. It is important to protect and preserve our environment so that the United States remains the United States."*). This narrative was also intertwined with representative images of participants' country of residence.

Binding moral foundations (submitted by Benjamin Douglas & Markus Brauer). This intervention relies on evoking ingroup-loyalty and authority moral foundations, which has been shown to increase support for pro-environmental behavior and attitudes (*61, 62*). Participants were asked to read the following text "*We are Americans [or participants' nationality, adapted for each country]. This means we can rise to any challenge that faces our country. From scientists to experts in the military, there is near universal agreement that climate change is real. The time to act is now. Using clean energy will help to keep our air, water, and land pure. It is the American [or participants' nationality, adapted for each country] solution to the climate crisis.*", after which they were exposed to an image of a person holding the national flag of participants' country of residence.

Exposure to effective collective action (Eric Shuman, Amit Goldenberg)**.** This intervention features examples of successful collective action that have had meaningful effects on climate policies, building on prior work showing that exposure to nonviolent action can increase willingness to join and maintain support (*63, 64*). In addition, prior work also found that highlighting the possibility of making real concrete changes through collective action can increase hope, efficacy, and collective action (*63*). Participants were exposed to a text explaining the impact people's actions can have on curbing the effects of climate change, citing research indicating there is still "*a window of opportunity"* to make a difference. Then participants were informed that the effectiveness of people's actions to fight climate change depends on their ability to "*come together and demand systemic change*". Participants were then exposed to several successful examples in which people solved global issues, such as the restoration of the ozone layer in 1987. Then participants were exposed to examples of climate activism initialized by individual people and leading to large scale movements or policy implementation (e.g., *protests by locals from the American Midwest against fossil fuels pressured the governors of Illinois, Indiana, Michigan, Minnesota, and Wisconsin to build a new network for charging electric vehicles*.). Images of concepts described in the text were displayed throughout.

Future-self-continuity (submitted by Vladimir Ponizovskiy, Lusine Grigoryan, Sonja Grelle, & Wilhelm Hofmann)**.** This intervention consists of emphasizing the future-self which has been found in prior work to motivate future-oriented behaviors, such as academic performance, ethical decision making, and pro-environmental behavior (*65-67*). Participants were asked to read a text emphasizing the importance of engaging in climate action (i.e., "*If no changes are made, the average temperature can increase by up to 6.5°C (12°F) by the year 2100 (IPCC, 2022). This would be extremely dangerous as super hurricanes, gigantic wildfires, and extreme food and water shortages would become commonplace.")*. They were then presented with a series of causes for this phenomenon (i.e., "*Human behaviors like energy production from fossil fuels, excessive meat consumption, and car driving increase the concentrations of greenhouse gasses in Earth's atmosphere. Over 90% of the increase in the world's temperature is caused by human activity*."). Finally, participants were asked to imagine their 2030 self is writing a letter to their present self, in which their future self is describing the actions they would have wanted to take regarding climate change (i.e., "*Please put yourself in the year 2030 - eight years from now. Take a few moments to imagine your life in that future. Imagine how you will look, where you will be, and who you are with. In the year 2030, it will be clear whether keeping climate change under 2°C is still possible. It will be clear whether the necessary change occurred fast enough to match the speed of the* *changing climate. As the Earth's atmosphere continues to heat up, the effects of climate change will be more apparent: the "highest observed temperature" records will keep being updated, heatwaves and the draughts will become more common, species will continue to become extinct. Now please write yourself a "letter from the future". This should be a letter you are writing in the year 2030, to your past self. As the person that you will be in 2030, what role would you think would be appropriate for you in respect to climate change? What would you want to tell yourself in the past? What would you like your past self to do? Please spend a bit of time on this task and try to write at least 100 words (5 sentences), or more, if possible.").*

Scientific consensus (submitted by Aart van Stekelenburg, Christian Klöckner, Stepan Vesely, Danielle Bleize)**.** This intervention consists of a message suggesting climate scientists are in agreement with each other that climate change is real and primarily caused by human action. Such messaging has been found to increase people's belief in climate change and support for climate mitigation policy (*58, 68*). Participants were exposed to the following text "*Did you know that 99% of expert climate scientists agree that the Earth is warming and climate change is happening, mainly because of human activity (for example, burning fossil fuels)? (Myers et al., 2021, Environmental Research Letters; Lynas et al., 2021, Environmental Research Letters; Doran et al., 2009, EOS)".* The text was accompanied by a pie chart with 99% of the surface area shaded.

Decreasing psychological distance (designed by Sarah Chamberlain, Don Hine, Guanxiong Huang). This intervention is based on prior work finding that many perceive climate change as psychologically distant (i.e., "*as a set of uncertain events that may occur far in the future, impacting distant places and affecting people dissimilar to themselves"*) (*10*)). Thus, framing climate change as a psychologically proximal risk issue (e.g., geographic) is expected to reduce psychological distance and increase public engagement. Participants were exposed to a paragraph emphasizing the impact of climate change (i.e., "*There is no doubt that humans are the main driver of climate change. Human influence has warmed the atmosphere, ocean, and land. Climate change is already affecting every region across the world. It has resulted in more frequent and intense extreme weather events, causing widespread harm and damage to people, wildlife and ecosystems. Human systems are being pushed beyond their ability to cope and adapt*."). They were then exposed to two examples of recent natural disasters caused by climate change in participants' region (e.g., US participants will be exposed to information about the 2021 record-breaking heat wave in North America causing the Lytton wildlife, and to information about the 2017 Hurricane Harvey in Texas and Hurricane Irma in Florida, killing 232 people and causing $175 billion in damage). Participants were then asked to select the aspects of their lives impacted by climate change from a list including: food production, farming and crop production, health and wellbeing, infectious disease, heat related harm and deaths, lack of, mental health issues, flooding and storms, changed land, freshwater and ocean environments, damaged infrastructure and economy. After making the selections, participants were provided the correct answers based on current scientific estimates (i.e., all the possible options). Finally, participants were asked to write about how climate change will affect them and their community (i.e., "*Please write in a few sentences: how those climate consequences will affect you, your friends and family, and your community. Try to imagine these things happening today so you can be specific and describe what it will be like.").*

Dynamic social norms (submitted by Oliver Genschow, David Loschelder, Gregg Sparkman, & Kimberly C. Doell)**.** This intervention is based on work showing that dynamic norms (i.e., how other people's behavior is changing over time) are even more impactful at changing behavior than static social norms (*69*). Participants in this intervention first read a paragraph emphasizing that "*People in the United States and around the world are changing: more and more people are concerned about climate change, and are now taking action across multiple fronts",* accompanied by an image featuring relevant data in support of this claim. Then participants were given examples of actions people are starting to take to mitigate the changing climate (i.e., "*Since 2013, concerns about climate change have increased in most countries surveyed. What kinds of actions are people taking right now? More than ever before, people are making changes to their lifestyles, supporting policies to address climate change, and are giving the issue more time and attention. For example, more and more people from around the world are now: cutting back on personal consumption, especially meat and dairy products, spending time, effort, and money on initiatives to mitigate climate change (for example, planting trees, offsetting carbon emissions), switching to low carbon modes of transportation (for example, taking bicycles). There's also been a notable increase in support for climate change mitigation policy–some of the most popular policies include: attempting to conserve forests and land, transitioning to solar, wind, and other renewable energy sources, creating/raising carbon taxes on fossil fuels, coal, gas, etc.").*

Correcting pluralistic ignorance (submitted by Michael Schmitt, Annika Lutz, & Jeff Lees). This intervention builds on work reporting that people substantially underestimate the climate change concern of others, a phenomenon labeled as "pluralistic ignorance" (*70*). Accordingly, collective action might be limited by people's misperception that not many people are concerned. This intervention presented real public opinion data that shows majorities around the world are concerned about climate change. Participants were first asked to predict the percent of people in their country who hold the belief that climate change is a global emergency (i.e., *Researchers recently conducted the "People's Climate Vote", which is the World's largest survey of public opinion on climate change ("global warming"). 1.2 million people completed the survey from 50 different countries around the globe. The survey included people from the United States. Think for a moment about Americans and their views on climate change. How many Americans do you think would agree with the statement "Climate change is a global emergency"?).* After providing a prediction, participants were shown the actual percentage of people in their country who hold the belief in question, according to The Peoples' Climate Vote (*71*). For example, participants in the United States will be told that "*The People's Climate Vote found that 65% of Americans agree that climate change is a global emergency".* For countries where the People's Climate Vote does not report national level results, participants were presented with the climate opinion of people in their region.

Letter to future generations (submitted by Stylianos Syropoulos, & Ezra Markowitz)**.** This intervention involves writing a letter to a member of the future generation, which has been shown to reduce the psychological distance between one's current choices and their consequences on future generations (*72, 73*). Participants were asked to write a letter to a child who will read it in the future (i.e., "*Please think of a child that is currently less than 5 years old (..) Now imagine that child is a 30 year old adult. It is approximately the year 2055, they have started a family of their own, and they are finding their own way in the world. Whether they recognize it or not, they live in a world that is powerfully shaped by the decisions we are all making now, in 2022. One day, (..) they find a letter written today, in 2022, which is a message from you.").* In this letter, participants are encouraged to write about their actions toward ensuring an inhabitable plant (*i.e.,"In it, you tell this family about all of the things you have done and want to do in the future to ensure that they will inherit a healthy, inhabitable planet. You tell them about your own personal efforts—however small or large—to confront the complex environmental problems of your time, from habitat loss to water pollution to climate change. In this letter you also tell this family in 2055 about how you want to be remembered by them and future generations as someone who did their best to ensure a safe, flourishing world.")*. Participants were allowed to write for 3 minutes and encouraged to write at least 100 words or 5 sentences.

Negative emotion (submitted by Kimberly Doell & Clara Pretus). This intervention involves exposure to scientific facts regarding the impacts of climate change in a 'doom and gloom' messaging style typically employed by climate communicators to induce negative emotions as a way of stimulating mitigation behaviors (*60*). Participants were first asked to report their baseline levels of emotions related to climate change, (e.g., hopeful, anxious, depressed, scared, indifferent, angry, helpless, guilty). They were then exposed to information about the consequences of climate change alongside representative images (e.g., "*Climate change is happening much more quickly, and will have a much greater impact, than climate scientists previously thought, according to the latest report by the Intergovernmental Panel on Climate Change (IPCC, 2022). If your anxiety about climate change is dominated by fears of starving polar bears, glaciers melting, and sea levels rising, you are barely scratching the surface of what terrors are possible, even within the lifetime of a young adult today. And yet the swelling seas — and the cities they will drown — have so dominated the picture of climate change/global warming that they have blinded us to other threats, many much closer at hand and much more catastrophic (...)")*. Finally, participants were asked to report their levels of emotions related to climate change again.

Control condition. Participants in the control condition were instructed to read a text retrieved from the novel Great Expectations by Charles Dickens (i.e., "*As soon as the great black velvet pall outside my little window was shot with grey, I got up and went downstairs; every board upon the way, and every crack in every board calling after me (...) I took it in the hope that it was not intended for early use, and would not be missed for some time.")*. Participants were required to spend at least 10 seconds reading this text. This was to ensure participants exerted some level of cognitive effort before being exposed to the dependent variable phase, to mirror the experience of participants in the experimental conditions. We chose a fiction text to prevent priming participants in any relevant way that could influence the dependent variables. After reading the excerpt, participants in the control condition were directed to the dependent variable phase, followed by the demographics phase. Finally, participants in the control condition were also directed to an additional independent variable phase, exclusive to participants in this condition.

Additional Variables Collected. These variables were only displayed to participants in the control condition, after they completed all dependent variables. First, participants were asked to rate the competence of climate scientists ("*On average, how competent are climate change research scientists?"*on a scale from 0=*Not at all* to 100=*Very much so*), their trust in scientific research about climate change ("*On average, how much do you trust scientific research about climate change?*" on a scale from 0=*Not at all* to 100=*Very much so*), their trust in their government ("*On average, how much do you trust your government?"* on a scale from 0=*Not at all* to 100=*Very much so*), their attitudes towards human welfare ("*To what degree do you see* *yourself as someone who cares about human welfare?"* on a scale from 0=*Not at all* to 100=*Very much so*), their global citizenship identity ("*To what degree do you see yourself as a global citizen?"* on a scale from 0=*Not at all* to 100=*Very much so*), their environmental identification (e.g., "*To what degree do you see yourself as someone who cares about the natural environment?"* on a scale from 0=*Not at all* to 100=*Very much so*), their extrinsic environmental motivation (e.g., "*Because of today's politically correct standards, I try to appear pro-environmental."* on a scale from 0=*Strongly disagree* to 100=*Strongly agree*). Then they were asked to estimate the percentage of people in their country who believe that climate change is a global emergency.

Statistical Methods

Our dependent variables have distributional properties (Fig S6) that preclude unbiased estimation with common, off-the-shelf, regression tools (such as the pre-registered analyses). To address this, estimates presented in the main text relied on Bayesian methods and custom likelihood functions. Full mathematical descriptions of all models can be found in the supplied code (https://github.com/josephbb/ManyLabsClimate). Additional analyses can be found at: https://github.com/mvlasceanu/ClimateTournament

Belief was estimated using a hierarchical Zero-One-Inflated Beta (ZOIB) model. This model was further used to derive adjusted participant-level estimates of pre-intervention belief, to avoid post-intervention bias in subsequent models. Sharing on social media was evaluated with a logistic regression. For WEPT, we used a geometric regression with a customized likelihood function to account for truncation and over-inflation for the maximum number of trees planted. Priors were selected using prior-predictive simulation, with model structure iteratively developed through analysis of the prior predictive distribution and validated through model comparison using posterior predictive simulation. Posteriors were sampled using a No-U-Turn Sampler (NUTS) implemented on a GPU with PyMC/NumPyro.

We note that these modeling choices are different from our pre-registered analysis, which specified linear (Belief, Policy), ordinal (WEPT), and logistic (Sharing) mixed-effects models. Plots of residuals from pre-registered models suggested moderate to severe violations of distributional assumptions. For this reason, *p*-values and estimates of effect sizes for these models may be unreliable. Despite these issues, we note the findings from pre-registered analyses are qualitatively similar to those from the Bayesian analyses. Overall, similarities between the pre-registered and Bayesian analyses suggest effects that are remarkably robust to analysis decisions.

For completeness, we include the results as pre-registered in Tables S9-S12 and Figure S1. Belief and Policy support were modeled using a linear mixed effects model with climate policy support, as the dependent variable, condition as the fixed effect, including item (9 policies), participant, and country as random effects. WEPT was modeled using an ordinal mixed effects model with climate action (WEPT), as the dependent variable, condition as the fixed effect, including country as random effects. Sharing was modeled using an ordinal mixed effects model with climate action (WEPT), as the dependent variable, condition as the fixed effect, including country as random effects.

To develop and evaluate our Bayesian models, we adapted an established Principle Bayesian Workflow (*74*). This process begins by identifying inference goals, domain knowledge, and features of the dataset. Candidate statistical models are proposed, with prior predictive checks are used to identify reasonable priors. Data are simulated from the prior predictive distribution, and the statistical model is fit to this simulated data. This allows for evaluation of computational properties of the model, tuning of the sampler, adjustment of the model or priors, and refinement. Key insight was gained through visual inspection of the posterior z-score vs. posterior contraction, which can indicate issues with overfit, underfit, bad prior models, or poorly identified model specification. This process was iterated on until a suitable candidate model and priors were identified. Finally, posterior predictive checks were used to verify that models adequately reconstructed broad properties of the data without regard to the estimands of interest (i.e., country/treatment effects). Failures here lead to adjustment of the underlying model. Once all model development criteria were satisfied, final analysis of the dataset was used to generate estimates of treatment and country level effects as well as all relevant figures. We note that priors for similar parameters across models may differ as a result of this iterative process, owing to distinct link functions and differing computational constraints. However, the impact of the prior on posterior samples is unlikely to be meaningful, given the volume of data.

We fit the selected model to the study data using PYMC (*75*) with a No U-Turn Sampler implemented on the GPU in NumPyro. We evaluated the model fit, ensuring the absence of divergent transitions, sufficient mixing of the (4) Markov chains, a large enough effective sample size, and an acceptable Estimated Bayesian Fraction of Missing Information (eBFMI). Finally, data were simulated from the posterior distribution and visual inspection of these posterior retrodictive checks were used to assess model fit. Sampling parameters were largely default, and can be found in the supplied code. .

Belief. Belief was indicated for four items on a scale from 0 to 100, inclusive. We scaled the outcome variable for each item to 0-1, to facilitate the use of common bound distributions. However, as both 0 and 1 were possible values, our likelihood function needed to account for possible inflation. As such, we implemented a hierarchical Zero-One-Inflated Beta (ZOIB) regression. We developed a generative model in which participants were estimated to have an unobserved pre-intervention belief, defined by their observed belief minus the estimated pre-intervention effect for their level of belief (i.e., as though they had been in the control condition). that was partially pooled by country, which in turn was partially pooled via a hyperparameter for average belief. Interventions were modeled with an intercept, corresponding to the average effect, and an effect of the estimated pre-intervention belief. The intervention effect and intercept for the control condition was fixed at zero. Otherwise, we modeled intervention effects using a multivariate normal distribution, to account for covariance between intercepts and interventions.

Further, we included partially pooled intercepts for item-specific effects. Where necessary, non-centered parameterizations were used to improve model fit.

Finally, we extracted the posterior average pre-intervention belief for each participant, to use in modeling Policy Support, Social Media Sharing, and WEPT. This reflects the observed level of belief, after adjusting for intervention effects on belief. As the treatment effects are small, these adjustments are minimal. Ideally, one would jointly model belief and other outcomes, however the large sample sizes inherent to a megastudy impose computational constraints, a particular issue with model development and evaluation. Extracting intervention-adjusted estimates of initial belief enables us to examine heterogeneous intervention effects for each of these outcomes, at a tractable degree of model complexity. We chose to focus on belief for evaluating heterogenous intervention effects under the assumption that belief is more likely to be a cause of support for policy, social media sharing, and investment in tree-planting activities than a consequence. Full mathematical descriptions of the model can be found in the supplied code.

Policy Support. Support for policy was indicated for nine items on a scale from 0 to 100, inclusive. Owing to computational constraints with the full dataset, we examined the average of these items. As with belief, this outcome was scaled from 0-1 and a ZOIB was used to model the data. Policy support was modeled with an intercept, an effect of adjusted belief, with intercept and belief effects modeled for interventions and countries. Intervention and country effects were modeled as separate zero-centered normal distributions.

Social Media Sharing. Sharing was a binary outcome, restricted to users who used social media. To analyze the impact on sharing, we relied on a Bayesian logistic regression. The probability of sharing was modeled with an intercept, an effect of adjusted belief, with intercept and belief effects modeled for interventions and countries. Intervention and country effects were modeled as separate zero-centered normal distributions.

WEPT Participants were able to plant between 1 and 8 trees. We began by modeling this as a truncated geometric distribution, assuming participants have a per-timestep chance of giving up and are forced to stop at 8. However, we noticed an over-abundance of planting eight trees consistent with some participants committing to planting all eight. Accordingly, we modified our likelihood to include inflation at 8 trees. Posterior predictive fits confirmed adequate model fit. With this likelihood, we constructed a Bayesian Hierarchical with an intercept, an effect of adjusted belief, and intercepts and belief effects modeled for interventions and countries.

References

1. IPCC, 2023, "*Climate Change 2023: Synthesis Report.* A Report of the Intergovernmental Panel on Climate Change. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change" (IPCC, Geneva, Switzerland, 2023).
2. D. Ivanova, J. Barrett, D. Wiedenhofer, B. Macura, M. Callaghan, F. Creutzig, Quantifying the potential for climate change mitigation of consumption options. *Environmental Research Letters* **15**, 093001 (2020).
3. R. Gifford, C. Kormos, A. McIntyre, Behavioral dimensions of climate change: drivers, responses, barriers, and interventions. *WIREs Climate Change*. **2**, 801–827 (2011).
4. I. M. Otto, J. F. Donges, R. Cremades, A. Bhowmik, R. J. Hewitt, W. Lucht, J. Rockström, F. Allerberger, M. McCaffrey, S. S. P. Doe, A. Lenferna, N. Morán, D. P. van Vuuren, H. J. Schellnhuber, Social tipping dynamics for stabilizing Earth's climate by 2050. *Proceedings of the National Academy of Sciences*. **117**, 2354–2365 (2020).
5. H. Allcott, S. Mullainathan, Behavior and Energy Policy. *Science*. **327**, 1204–1205 (2010).
6. S. Carattini, S. Kallbekken, A. Orlov, How to win public support for a global carbon tax. *Nature*. **565**, 289–291 (2019).
7. M. A. Jenny, C. Betsch, Large-scale behavioural data are key to climate policy. *Nature Human Behavior.* **6**, 1444–1447 (2022).
8. J. W. Composto, E. U. Weber, Effectiveness of behavioural interventions to reduce household energy demand: A scoping review. *Environmental Research Letters*. **17**, 063005 (2022).
9. C. F. Nisa, J. J. Bélanger, B. M. Schumpe, D. G. Faller, Meta-analysis of randomised controlled trials testing behavioural interventions to promote household action on climate change. *Nature Communications*. **10**, 4545 (2019).
10. C. Jones, D. W. Hine, A. D. G. Marks, The future is now: Reducing psychological distance to increase public engagement with climate change. *Risk Analysis*. **37**, 331–341 (2017).
11. L. C. Howe, P. B. Carr, G. M. Walton, Normative appeals motivate people to contribute to collective action problems more when they invite people to work together toward a common goal. *Journal of Personality and Social Psychology*. **121**, 215–238 (2021).
12. C. J. Clark, T. Costello, G. Mitchell, P. E. Tetlock, Keep your enemies close: Adversarial collaborations will improve behavioral science. *Journal of Applied Research in Memory and Cognition*. **11**, 1–18 (2022).
13. D. Kahneman, Experiences of collaborative research. *American Psychologist*. **58**, 723–730 (2003).
14. S. Benartzi, J. Beshears, K. L. Milkman, C. R. Sunstein, R. H. Thaler, M. Shankar, W. Tucker-Ray, W. J. Congdon, S. Galing, Should Governments Invest More in Nudging? *Psychological Science*. **28**, 1041–1055 (2017).
15. A. L. Duckworth, K. L. Milkman, A guide to megastudies. *PNAS Nexus*. **1**, pgac214 (2022).
16. M. Bergquist, M. Thiel, M. H. Goldberg, S. van der Linden, Field interventions for climate change mitigation behaviors: A second-order meta-analysis. *Proceedings of the National Academy of Sciences*. **120**, e2214851120 (2023).
17. K. C. Doell, Megastudies to test the efficacy of behavioural interventions. *Nature Reviews Psychology*. **2**, 263–263 (2023).
18. K. L. Milkman, D. Gromet, H. Ho, J. S. Kay, T. W. Lee, P. Pandiloski, Y. Park, A. Rai, M. Bazerman, J. Beshears, L. Bonacorsi, C. Camerer, E. Chang, G. Chapman, R. Cialdini, H. Dai, L. Eskreis-Winkler, A. Fishbach, J. J. Gross, S. Horn, A. Hubbard, S. J. Jones, D. Karlan, T. Kautz, E. Kirgios, J. Klusowski, A. Kristal, R. Ladhania, G. Loewenstein, J. Ludwig, B. Mellers, S. Mullainathan, S. Saccardo, J. Spiess, G. Suri, J. H. Talloen, J. Taxer, Y. Trope, L. Ungar, K. G. Volpp, A. Whillans, J. Zinman, A. L. Duckworth, Megastudies improve the impact of applied behavioural science. *Nature*. **600**, 478–483 (2021).

19. A. M. van Valkengoed, W. Abrahamse, L. Steg, To select effective interventions for pro-environmental behaviour change, we need to consider determinants of behaviour. *Nature Human Behavior.* **6**, 1482–1492 (2022).
20. J. Henrich, S. J. Heine, A. Norenzayan, Most people are not WEIRD. *Nature*. **466**, 29–29 (2010).
21. K. C. Doell, P. Pärnamets, E. A. Harris, L. M. Hackel, J. J. Van Bavel, Understanding the effects of partisan identity on climate change. *Current Opinion in Behavioral Sciences*. **42**, 54–59 (2021).
22. M. J. Hornsey, E. A. Harris, K. S. Fielding, Relationships among conspiratorial beliefs, conservatism and climate scepticism across nations. *Nature Climate Change*. **8**, 614–620 (2018).
23. L. Chancel, Global carbon inequality over 1990–2019. *Nature Sustainability*. **5**, 931–938 (2022).
24. J. J. Van Bavel, A. Cichocka, V. Capraro, H. Sjåstad, J. B. Nezlek, T. Pavlović, M. Alfano, M. J. Gelfand, F. Azevedo, M. D. Birtel, A. Cislak, P. L. Lockwood, R. M. Ross, K. Abts, E. Agadullina, J. J. B. Aruta, S. N. Besharati, A. Bor, B. L. Choma, C. D. Crabtree, W. A. Cunningham, K. De, W. Ejaz, C. T. Elbaek, A. Findor, D. Flichtentrei, R. Franc, B. Gjoneska, J. Gruber, E. Gualda, Y. Horiuchi, T. L. D. Huynh, A. Ibanez, M. A. Imran, J. Israelashvili, K. Jasko, J. Kantorowicz, E. Kantorowicz-Reznichenko, A. Krouwel, M. Laakasuo, C. Lamm, C. Leygue, M.-J. Lin, M. S. Mansoor, A. Marie, L. Mayiwar, H. Mazepus, C. McHugh, J. P. Minda, P. Mitkidis, A. Olsson, T. Otterbring, D. J. Packer, A. Perry, M. B. Petersen, A. Puthillam, J. C. Riaño-Moreno, T. Rothmund, H. Santamaría-García, P. C. Schmid, D. Stoyanov, S. Tewari, B. Todosijević, M. Tsakiris, H. H. Tung, R. G. Umbreş, E. Vanags, M. Vlasceanu, A. Vonasch, M. Yucel, Y. Zhang, M. Abad, E. Adler, N. Akrawi, H. A. Mdarhri, H. Amara, D. M. Amodio, B. G. Antazo, M. Apps, F. C. Ay, M. H. Ba, S. Barbosa, B. Bastian, A. Berg, M. P. Bernal-Zárate, M. Bernstein, M. Białek, E. Bilancini, N. Bogatyreva, L. Boncinelli, J. E. Booth, S. Borau, O. Buchel, C. D. Cameron, C. F. Carvalho, T. Celadin, C. Cerami, H. N. Chalise, X. Cheng, L. Cian, K. Cockcroft, J. Conway, M. A. Córdoba-Delgado, C. Crespi, M. Crouzevialle, J. Cutler, M. Cypryańska, J. Dabrowska, M. A. Daniels, V. H. Davis, P. N. Dayley, S. Delouvee, O. Denkovski, G. Dezecache, N. A. Dhaliwal, A. B. Diato, R. Di Paolo, M. Drosinou, U. Dulleck, J. Ekmanis, A. S. Ertan, T. W. Etienne, H. H. Farhana, F. Farkhari, H. Farmer, A. Fenwick, K. Fidanovski, T. Flew, S. Fraser, R. B. Frempong, J. A. Fugelsang, J. Gale, E. B. Garcia-Navarro, P. Garladinne, O. Ghajjou, T. Gkinopoulos, K. Gray, S. M. Griffin, B. Gronfeldt, M. Gümren, R. L. Gurung, E. Halperin, E. Harris, V. Herzon, M. Hruška, G. Huang, M. F. C. Hudecek, O. Isler, S. Jangard, F. J. Jørgensen, F. Kachanoff, J. Kahn, A. K. Dangol, O. Keudel, L. Koppel, M. Koverola, E. Kubin, A. Kunnari, Y. Kutiyski, O. Laguna, J. Leota, E. Lermer, J. Levy, N. Levy, C. Li, E. U. Long, C. Longoni, M. Maglić, D. McCashin, A. L. Metcalf, I. Mikloušić, S. El Mimouni, A. Miura, J. Molina-Paredes, C. Monroy-Fonseca, E. Morales-Marente, D. Moreau, R. Muda, A. Myer, K. Nash, T. Nesh-Nash, J. P. Nitschke, M. S. Nurse, Y. Ohtsubo, V. Oldemburgo de Mello, C. O'Madagain, M. Onderco, M. S. Palacios-Galvez, J. Palomäki, Y. Pan, Z. Papp, P. Pärnamets, M. Paruzel-Czachura, Z. Pavlović, C. Payán-Gómez, S. Perander, M. M. Pitman, R. Prasad, J. Pyrkosz-Pacyna, S. Rathje, A. Raza, G. G. Rêgo, K. Rhee, C. E. Robertson, I. Rodríguez-Pascual, T. Saikkonen, O. Salvador-Ginez, W. M. Sampaio, G. C. Santi, N. Santiago-Tovar, D. Savage, J. A. Scheffer, P. Schönegger, D. T. Schultner, E. M. Schutte, A. Scott, M. Sharma, P. Sharma, A. Skali, D. Stadelmann, C. A. Stafford, D. Stanojević, A. Stefaniak, A. Sternisko, A. Stoica, K. K. Stoyanova, B. Strickland, J. Sundvall, J. P. Thomas, G. Tinghög, B. Torgler, I. J. Traast, R. Tucciarelli, M. Tyrala, N. D. Ungson, M. S. Uysal, P. A. M. Van Lange, J.-W. van Prooijen, D. van Rooy, D. Västfjäll, P. Verkoeijen, J. B. Vieira, C. von Sikorski, A. C. Walker, J. Watermeyer, E. Wetter, A. Whillans, R. Willardt, M. J. A. Wohl, A. D. Wójcik, K. Wu, Y. Yamada, O. Yilmaz, K. Yogeeswaran, C.-T. Ziemer, R. A. Zwaan, P. S. Boggio, National identity predicts public health support during a global pandemic. *Nature Communications*. **13**, 517 (2022).
25. E. L. Uhlmann, C. R. Ebersole, C. R. Chartier, T. M. Errington, M. C. Kidwell, C. K. Lai, R. J. McCarthy, A. Riegelman, R. Silberzahn, B. A. Nosek, Scientific utopia III: Crowdsourcing science. *Perspectives on Psychological Science*. **14**, 711–733 (2019).

26. M. J. Hornsey, E. A. Harris, P. G. Bain, K. S. Fielding, Meta-analyses of the determinants and outcomes of belief in climate change. *Nature Climate Change*. **6**, 622–626 (2016).
27. A. J. Yeganeh, A. P. McCoy, T. Schenk, Determinants of climate change policy adoption: A meta-analysis. *Urban Climate*. **31**, 100547 (2020).
28. N. Chater, G. Loewenstein, The i-frame and the s-frame: How focusing on individual-level solutions has led behavioral public policy astray. *Behavioral and Brain Sciences*, 1–60 (2022).
29. M. Fairbrother, Public opinion about climate policies: A review and call for more studies of what people want. *PLOS Climate*. **1**, e0000030 (2022).
30. Nielsen, K. S., Cologna, V., Lange, F., Brick, C., & Stern, P. C. (2021). The case for impact-focused environmental psychology. *Journal of Environmental Psychology*, January, 10–12. https://doi.org/10.1016/j.jenvp.2021.101559
31. F. Creutzig, L. Niamir, X. Bai, M. Callaghan, J. Cullen, J. Díaz-José, M. Figueroa, A. Grubler, W. F. Lamb, A. Leip, E. Masanet, É. Mata, L. Mattauch, J. C. Minx, S. Mirasgedis, Y. Mulugetta, S. B. Nugroho, M. Pathak, P. Perkins, J. Roy, S. de la Rue du Can, Y. Saheb, S. Some, L. Steg, J. Steinberger, D. Ürge-Vorsatz, Demand-side solutions to climate change mitigation consistent with high levels of well-being. *Nature Climate Change.* **12**, 36–46 (2022).
32. E. Salomon, J. L. Preston, M. B. Tannenbaum, Climate change helplessness and the (de)moralization of individual energy behavior. *Journal of Experimental Psychology: Applied*. **23**, 15–28 (2017).
33. Simpson, B. (2006). Social identity and cooperation in social dilemmas. *Rationality and society*, 18(4), 443-470.
34. W. J. Brady, J. A. Wills, J. T. Jost, J. A. Tucker, J. J. Van Bavel, Emotion shapes the diffusion of moralized content in social networks. *Proceedings of the National Academy of Sciences*. **114**, 7313–7318 (2017).
35. K. Hayhoe, *Saving Us* (Atria/One Signal Publishers, 2022).
36. C. Kormos, R. Gifford, The validity of self-report measures of proenvironmental behavior: A meta-analytic review. *Journal of Environmental Psychology.* **40**, 359–371 (2014).
37. F. Lange, S. Dewitte, The Work for Environmental Protection Task: A consequential web-based procedure for studying pro-environmental behavior. *Behavior Research Methods*. **54**, 133–145 (2022).
38. L. R. Glasman, D. Albarracín, Forming attitudes that predict future behavior: a meta-analysis of the attitude-behavior relation. *Psychological Bulletin*. **132**, 778–822 (2006).
39. F. Lange, Behavioral paradigms for studying pro-environmental behavior: A systematic review. *Behavior Research Methods*. **55**, 600–622 (2023).
40. P. Sheeran, T. L. Webb, The Intention–Behavior Gap. *Social and Personality Psychology Compass*. **10**, 503–518 (2016).
41. L. Hespanhol, C. S. Vallio, L. M. Costa, B. T. Saragiotto, Understanding and interpreting confidence and credible intervals around effect estimates. *Brazilian Journal of Physical Therapy.* **23,** 290-301 (2019).
42. K. C. Doell, L. Lengersdorff, S. A. Rhoads, B. Todorova, J. P. Nitschke, J. Druckman, M. Vlasceanu, Manylabs Climate Consortia, C. Lamm, J. J. Van Bavel, Academics are more accurate at predicting the efficacy of climate action interventions for outcomes with more recent scientific investigation. [Manuscript in prep].
43. T. Toles, Opinion | Doomsday scenarios are as harmful as climate change denial. *Washington Post* (2017), (available at https://www.washingtonpost.com/opinions/doomsday-scenarios-are-as-harmful-as-climate-change-denial/2017/07/12/880ed002-6714-11e7-a1d7-9a32c91c6f40_story.html).
44. C. E. Robertson, N. Pröllochs, K. Schwarzenegger, P. Pärnamets, J. J. Van Bavel, S. Feuerriegel, Negativity drives online news consumption. *Nature Human Behavior*, 1–11 (2023).
45. K. C. Doell, B. Conte, T. Brosch, Interindividual differences in environmentally relevant positive trait affect impacts sustainable behavior in everyday life. *Scientific Reports*. **11**, 20423 (2021).

46. D. A. Chapman, B. Lickel, E. M. Markowitz, Reassessing emotion in climate change communication. *Nature Climate Change*. **7**, 850–852 (2017).
47. A. Coppock, T. J. Leeper, K. J. Mullinix, Generalizability of heterogeneous treatment effect estimates across samples. *Proceedings of the National Academy of Sciences.* **115**, 12441-12446 (2018).
48. A. Coppock, *Persuasion in Parallel: How Information Changes Minds about Politics* (Chicago: The University of Chicago Press, 2022).
49. K. J. Mullinix, T. J. Leeper, J. N. Druckman, J. Freese, The Generalizability of Survey Experiments. *Journal of Experimental Political Science.* **2**, 109-138, (2015).
50. J. D. Weinberg, J. Freese, D. McElhattan, Comparing Data Characteristics and Results of an Online Factorial Survey between a Population-Based and a Crowdsource-Recruited Sample. *Sociological Science.* **1,** 292-310 (2014).
51. E. T. Berkman, S. M. Wilson, So useful as a good theory? The practicality crisis in (social) psychological theory. *Perspectives on Psychological Science.* **16**, 864–874 (2021).
52. A. G. Thalmayer., C. Toscanelli, J. J. Arnett, The neglected 95% revisited: Is American psychology becoming less American? *American. Psychologist.* **76**, 116–129 (2021).
53. S. Beck, T. Brasseur, M. Poetz, H. Sauermann, Crowdsourcing research questions in science. *Research Policy.* **51**, 104491 (2022).
54. K. C. Doell, Megastudies to test the efficacy of behavioural interventions. *Nature Reviews Psychology*. **2**, 263 (2023).
55. A. J. Berinsky, M. F. Margolis, &M. W. Sances, Separating the Shirkers from the Workers? Making Sure Respondents Pay Attention on Self-Administered Surveys. *American Journal of Political Science*. **58**, 739–753 (2014).
56. A. Baranzini, J. C. J. M. van den Bergh, S. Carattini, R. B. Howarth, E. Padilla, J. Roca, Carbon pricing in climate policy: seven reasons, complementary instruments, and political economy considerations. *WIREs Climate Change*. **8**, e462 (2017).
57. J. T. Jost, *A Theory of System Justification* (Harvard University Press, 2020).
58. S. L. van der Linden, A. A. Leiserowitz, G. D. Feinberg, E. W. Maibach, The Scientific Consensus on Climate Change as a Gateway Belief: Experimental Evidence. *PLOS ONE*. **10**, e0118489 (2015).
59. F. G. Kaiser, M. Wilson, Goal-directed conservation behavior: The specific composition of a general performance. *Personality and Individual Differences.* **36**, 1531-1544 (2004).
60. I. Feygina, J. T. Jost, R. E. Goldsmith, System Justification, the Denial of Global Warming, and the Possibility of "System-Sanctioned Change." *Personality and Social Psychology Bulletin*. **36**, 326–338 (2010).
61. M. Feinberg, R. Willer, Moral reframing: A technique for effective and persuasive communication across political divides. *Social and Personality Psychology Compass*. **13** (2019), doi:10.1111/spc3.12501.
62. C. Wolsko, H. Ariceaga, J. Seiden, Red, white, and blue enough to be green: Effects of moral framing on climate change attitudes and conservation behaviors. *Journal of Experimental Social Psychology*. **65**, 7–19 (2016).
63. A. Goldenberg, S. Cohen-Chen, J. P. Goyer, C. S. Dweck, J. J. Gross, E. Halperin, Testing the impact and durability of a group malleability intervention in the context of the Israeli–Palestinian conflict. *PNAS Proceedings of the National Academy of Sciences of the United States of America*. **115**, 696–701 (2018).
64. E. Shuman, T. Saguy, M. van Zomeren, E. Halperin, Disrupting the system constructively: Testing the effectiveness of nonnormative nonviolent collective action. *Journal of Personality and Social Psychology*. **121**, 819–841 (2021).

65. R. M. Adelman, S. D. Herrmann, J. E. Bodford, J. E. Barbour, O. Graudejus, M. A. Okun, V. S. Y. Kwan, Feeling Closer to the Future Self and Doing Better: Temporal Psychological Mechanisms Underlying Academic Performance. *Journal of Personality*. **85**, 398–408 (2017).
66. H. E. Hershfield, T. R. Cohen, L. Thompson, Short horizons and tempting situations: Lack of continuity to our future selves leads to unethical decision making and behavior. *Organizational Behavior and Human Decision Processes*. **117**, 298–310 (2012).
67. C. Nurra, D. Oyserman, From future self to current action: An identity-based motivation perspective. *Self and Identity*. **17**, 343–364 (2018).
68. J. B. Rode, S. Iqbal, B. J. Butler, P. H. Ditto, Using a News Article to Convey Climate Science Consensus Information. *Science Communication*. **43**, 651–673 (2021).
69. G. Sparkman, G. M. Walton, Dynamic Norms Promote Sustainable Behavior, Even if It Is Counternormative. *Psychological Science*. **28**, 1663–1674 (2017).
70. N. Geiger, J. K. Swim, Climate of silence: Pluralistic ignorance as a barrier to climate change discussion. *Journal of Environmental Psychology*. **47**, 79–90 (2016).
71. The Peoples' Climate Vote | United Nations Development Programme. *UNDP*, (available at https://www.undp.org/publications/peoples-climate-vote).
72. T. R. Shrum, The salience of future impacts and the willingness to pay for climate change mitigation: an experiment in intergenerational framing. *Climatic Change*. **165**, 1–20 (2021).
73. R. H. Wickersham, L. Zaval, N. A. Pachana, M. A. Smyer, The impact of place and legacy framing on climate action: A lifespan approach. *PLOS ONE*. **15**, e0228963 (2020).
74. D. J. Schad, M. Betancourt, S. Vasishth, Toward a principled Bayesian workflow in cognitive science. *Psychological Methods*. **26**, 103–126 (2021).
75. J. Salvatier, T. V. Wiecki, C. Fonnesbeck, Probabilistic programming in Python using PyMC3. *PeerJ Computer Science.* **2**, e55 (2016).

Acknowledgements

Funding

Google Jigsaw grant (Madalina Vlasceanu; Kimberly C. Doell; Jay J. Van Bavel)
Swiss National Science Foundation P400PS_190997 (Kimberly C. Doell)
Dutch Research Council grant 7934 (Karlijn L. van den Broek)
John Templeton Foundation grant 61378 (Mark Alfano)
The National Council for Scientific and Technological Development grant (Angélica Andersen)
Christ Church College Research Centre grant (Matthew A. J. Apps)
David Phillips Fellowship grant BB/R010668/2 (Matthew A. J. Apps)
Jacobs Foundation Fellowship (Matthew A. J. Apps)
"DFG grant project no. 390683824 (Moritz A. Drupp; Piero Basaglia; Björn Bos)"
NYUAD research funds (Jocelyn J. Bélanger)
"The Swiss Federal Office of Energy through the ""Energy, Economy, and Society"" program grant number: SI/502093-01 (Sebastian Berger)"

The Belgian National Fund for Scientific Research (FRS-FNRS) PDR 0253.19 (Paul Bertin)
Fund for scientific development at the Faculty of Psychology at SWPS University in Warsaw (Olga Bialobrzeska)
Radboud University Behavioural Science Institute (Daniëlle N. M. Bleize)
"Leuphana University Lüneburg research fund (David D. Loschelder; Lea Boecker; Yannik A. Escher; Hannes M. Petrowsky; Meikel Soliman)"
University of Birmingham Start up Seed Grant (Ayoub Bouguettaya)
Prime-Pump Fund from University of Birmingham (Ayoub Bouguettaya; Mahmoud Elsherif)
University of Geneva Faculty Seed Funding (Tobias Brosch)
"Pomona College Hirsch Research Initiation Grant (Adam R. Pearson)"
Center for Social Conflict and Cohesion Studies grant ANID/FONDAP #15130009 (Héctor Carvacho; Silvana D'Ottone)
Center for Intercultural and Indigenous Research grant ANID/FONDAP #15110006 (Héctor Carvacho; Silvana D'Ottone)
National Research Foundation of Korea NRF-2020S1A3A2A02097375 (Dongil Chung; Sunhae Sul)
Darden School of Business (Luca Cian)
Kieskompas - Election Compass (Tom W. Etienne; Andre P. M. Krouwel; Vladimir Cristea; Alberto López Ortega)
The National Agency of Research and Development, National Doctoral Scholarship 24210087 (Silvana D'Ottone)
Dutch Science Foundation (NWO) grant VI.Veni.201S.075 (Marijn H.C. Meijers)
The Netherlands Organization for Scientific Research (NWO) Vici grant 453-15-005 (Iris Engelhard)
Foundation for Science and Technology – FCT (Portuguese Ministry of Science, Technology and Higher Education) grant UIDB/05380/2020 (Ana Rita Farias)
The Slovak Research and Development Agency (APVV) contract no. APVV-21-0114 (Andrej Findor)
The James McDonnell Foundation 21st Century Science Initiative in Understanding Human Cognition—Scholar Award grant 220020334 (Lucia Freira; Joaquin Navajas)
Sponsored Research Agreement between Meta and Fundación Universidad Torcuato Di Tella grant INB2376941 (Lucia Freira; Joaquin Navajas)
Thammasat University Fast Track Research Fund (TUFT) 12/2566 (Neil Philip Gains)
HSE University Basic Research Program (Dmitry Grigoryev; Albina Gallyamova)
ARU Centre for Societies and Groups Research Centre Development Funds (Sarah Gradidge; Annelie J. Harvey; Magdalena Zawisza)
University of Stavanger faculty of Social Science research activities grant (Simone Grassini)
Center for the Science of Moral Understanding (Kurt Gray)
University of Colorado Boulder Faculty research fund (June Gruber)
Swiss National Science Foundation grant 203283 (Ulf J.J. Hahnel)

Kochi University of Technology Research Funds (Toshiyuki Himichi)
RUB appointment funds (Wilhelm Hofmann)
Dean's Office, College of Arts and Sciences at Seton Hall University (Fanli Jia)
Nicolaus Copernicus University (NCU) budget (Dominika Jurgiel; Adrian Dominik Wojcik)
Sectorplan Social Sciences and Humanities, The Netherlands (Elena Kantorowicz-Reznichenko)
Erasmus Centre of Empirical Legal Studies (ECELS), Erasmus School of Law, Erasmus University Rotterdam, The Netherlands (Elena Kantorowicz-Reznichenko)
American University of Sharjah Faculty Research Grant 2020 FRG20-M-B134 (Ozgur Kaya; Ilker Kaya)
Centre for Social and Early Emotional Development SEED grant (Anna Klas; Emily J. Kothe)
ANU Futures Grant (Colin Klein)
Research Council of Norway through Centres of Excellence Scheme, FAIR project No 262675 (Hallgeir Sjåstad and Simen Bø)
Aarhus University Research Foundation grant AUFF-E-2021-7-16 (Ruth Krebs; Laila Nockur)
Social Perception and Intergroup Inequality Lab at Cornell University (Amy R. Krosch)
COVID-19 Rapid Response grant, University of Vienna (Claus Lamm)
Austrian Science Fund FWF I3381 (Claus Lamm)
FWO Postdoctoral Fellowship 12U1221N (Florian Lange)
National Geographic Society (Julia Lee Cunningham)
University of Michigan Ross School of Business Faculty Research Funds (Julia Lee Cunningham)
The Clemson University Media Forensics Hub (Jeffrey Lees)
John Templeton Foundation grant 62631 (Neil Levy; Robert M. Ross)
ARC Discovery Project DP180102384 (Neil Levy)
Medical Research Council Fellowship grant MR/P014097/1 (Patricia L. Lockwood)
Medical Research Council Fellowship grant MR/P014097/2 (Patricia L. Lockwood)
Jacobs Foundation (Patricia L. Lockwood)
Wellcome Trust and the Royal Society Sir Henry Dale Fellowship grant 223264/Z/21/Z (Patricia L. Lockwood)
JFRAP grant (Jackson G. Lu)
Social Sciences and Humanities Research Council (SSHRC) Doctoral Fellowship (Yu Luo)
Simon Fraser University Psychology Department Research Grant (Annika E. Lutz; Michael T. Schmitt)
GU internal funding (Abigail A. Marsh; Shawn A. Rhoads)
FAPESP 2014/50279-4 (Karen Louise Mascarenhas)
FAPESP 2020/15230-5 (Karen Louise Mascarenhas)
Shell Brasil (Karen Louise Mascarenhas)
Brazil's National Oil, Natural Gas and Biofuels Agency (ANP) through the R&D levy regulation (Karen Louise Mascarenhas)
ANR grant SCALUP, ANR-21-CE28-0016-01 (Hugo Mercier)

NOMIS Foundation grant for the Centre for the Politics of Feelings (Katerina Michalaki; Manos Tsakiris)
"Applied Moral Psychology Lab at Cornell University (Sarah Milliron; Laura Niemi; Magdalena Zawisza)"
Universidad Peruana Cayetano Heredia Project 209465 (Fredy S. Monge-Rodríguez)
Belgian National Fund for Scientific Research (FRS-FNRS) grant PDR 0253.19 (Youri L. Mora)
Riksbankens Jubileumsfond grant P21-0384 (Gustav Nilsonne)
European Research Council funded by the UKRI Grant EP/X02170X/1 (Maria Serena Panasiti; Giovanni Antonio Travaglino)
Statutory Funding of Institute of Psychology, University of Silesia in Katowice (Mariola Paruzel-Czachura)
Aarhus University Research Foundation AUFF-E-2018-7-13 (Stefan Pfattheicher)
São Paulo Research Foundation (FAPESP) grant 2019/26665-5 (Gabriel G. Rêgo)
Mistletoe Unfettered Research Grant, National Science Foundation GRFP Award 1937959 (Shawn A. Rhoads)
Japan Society for the Promotion of Science grant 21J01224 (Toshiki Saito)
Institute of Psychology & the Faculty of Social and Political Sciences, University of Lausanne (Oriane Sarrasin)
Universitat Ramon Llull, Esade Business School (Katharina Schmid)
University of St Andrews (Philipp Schoenegger)
Dutch Science Foundation (NWO) VI.Veni.191G.034 (Christin Scholz)
Universität Hamburg (Stefan Schulreich)
Faculty of Health PhD fellowship, Aarhus University (Katia Soud)
School of Medicine and Psychology, Australian National University (Samantha K. Stanley)
Swedish Research Council grant 2018-01755 (Gustav Tinghög)
Russian Federation Government grant project 075-15-2021-611 (Danila Valko)
Swedish Research Council (Daniel Västfjäll)
Cooperatio Program MCOM (Marek Vranka)
Stanford Center on Philanthropy and Civil Society (Robb Willer)
Canada Research Chairs program (Jiaying Zhao)

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Competing Interests

André Krouwel (Departments of Political Science and Communication Science at Vrije Universiteit Amsterdam) is founder and stockholder of Kieskompas (data collection service), but has not financially benefited from this data collection or study.

Data and Materials Availability

All data and code can be found on GitHub: https://github.com/josephbb/ManyLabsClimate and https://github.com/mvlasceanu/ClimateTournament

The interventions (in each language) can be accessed as qsf files (to be imported in Qualtrics): https://osf.io/ytf89/files/osfstorage/6454f8d771778511d9b0f48f.

A webtool for rapidly assessing which intervention is most likely to be effective at increasing climate change beliefs, policy support, information sharing, and tree planting efforts, for any subsample target of interest, varying along demographics such as nationality, political ideology, age, gender, education, or income level can be found here: https://climate-interventions.shinyapps.io/climate-interventions/

Supplemental Analyses and Figures

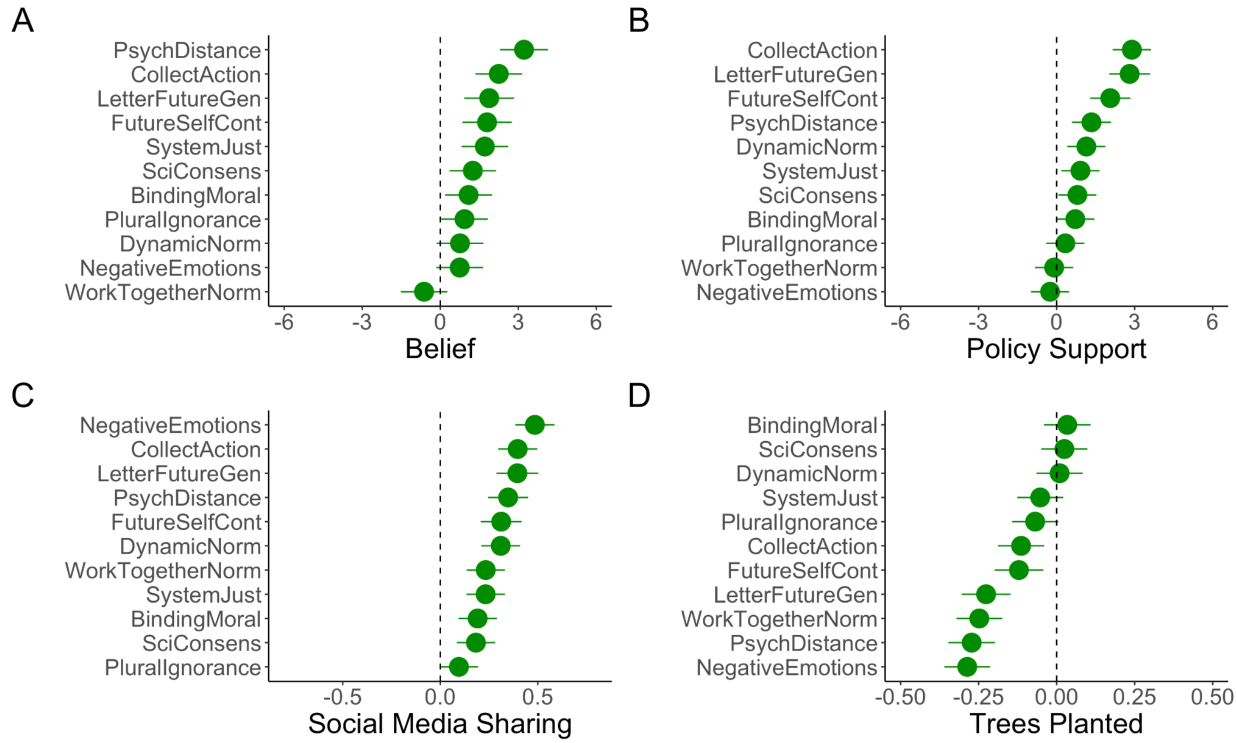

Figure S1: Coefficient estimates and 95% confidence intervals average treatment effects in the pre-registered analysis. A) Belief B) Policy Support C) Social Media Sharing D) Trees Planted (N=59,440 participants in 63 countries).

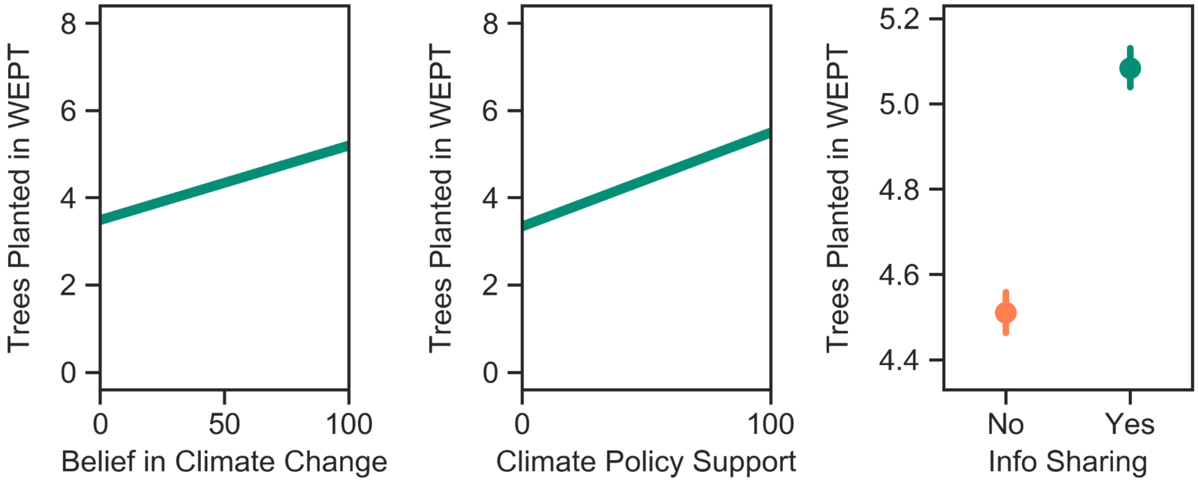

Figure S2: Number of trees planted in the WEPT as a function of belief in climate change, climate policy support, and willingness to share climate information. Statistics of the mixed models conducted are reported in tables S13-S18. The results reveal positive associations between the first three (lower effort behavioral) outcomes and the higher effort action (WEPT).

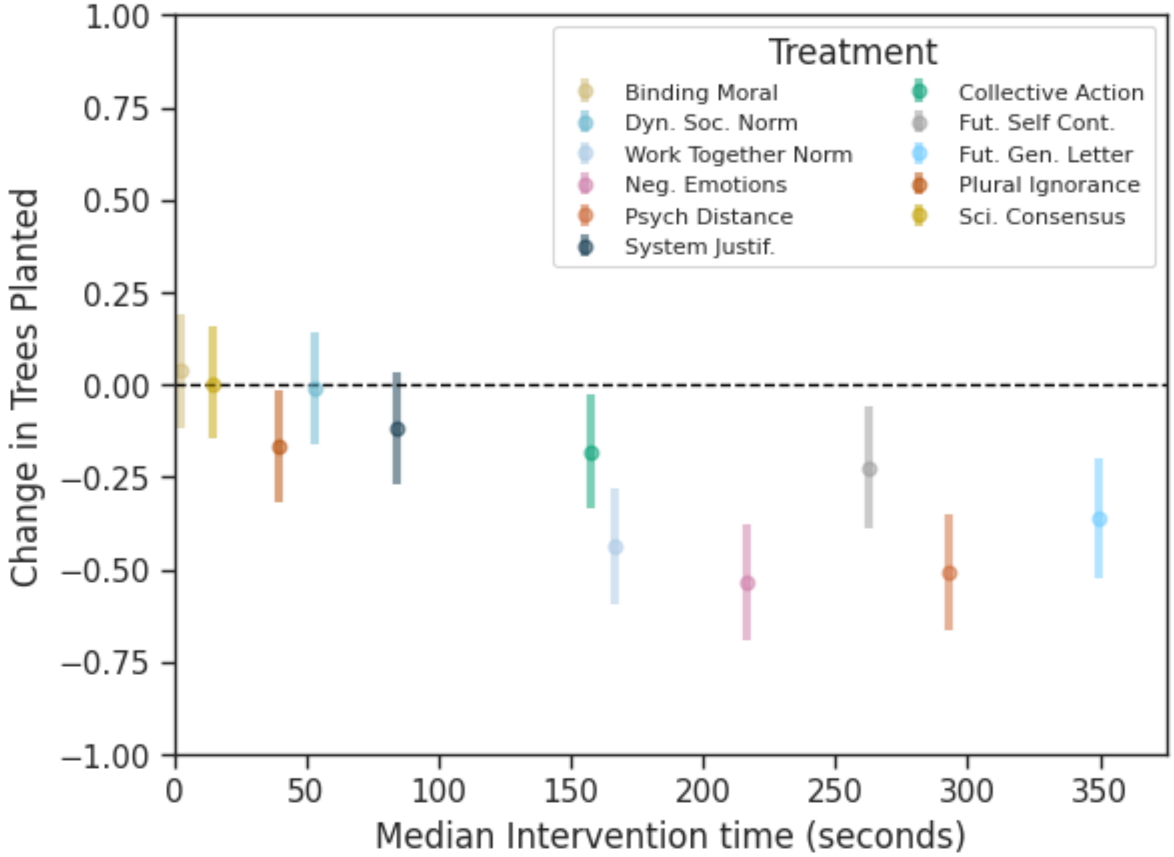

Fig S3: Average intervention effects for WEPT as a function of median intervention time.

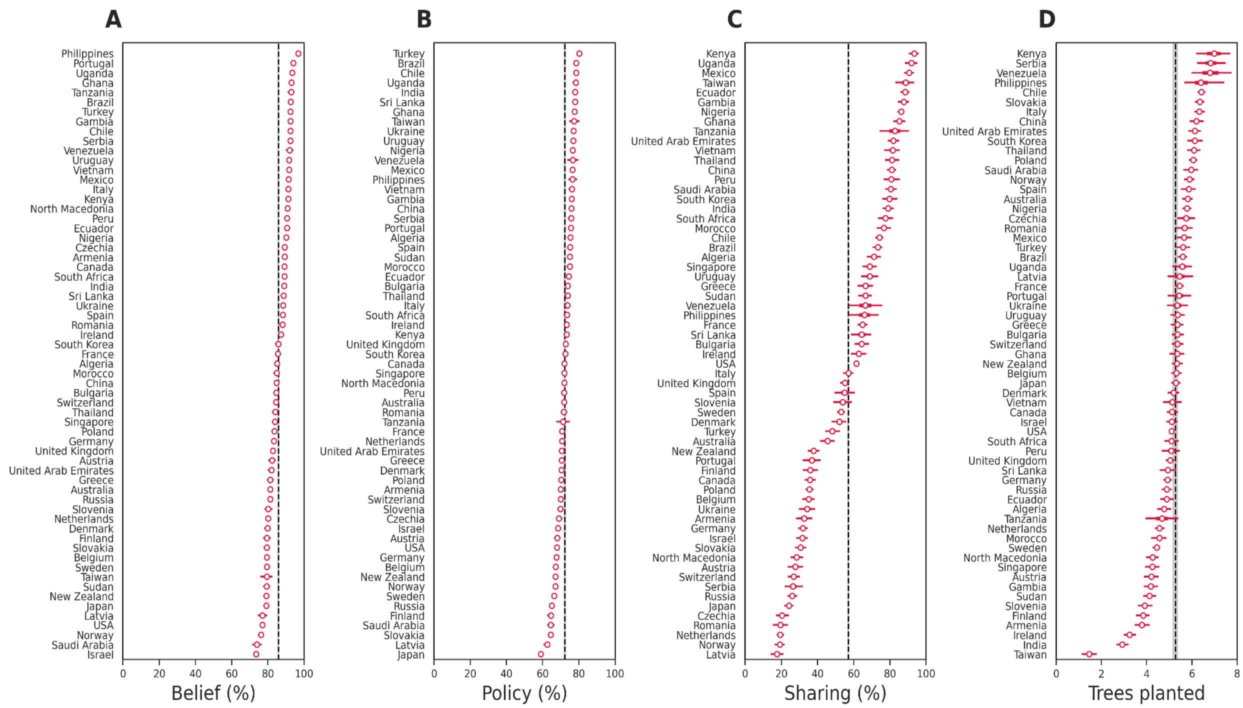

Fig S4: Country-level effects. Marginal, country-level posterior estimates for each of the key dependent variables. Dots indicate the mean, with error bars indicating the 94% credible region (C.R.). Thicker bars, when visible, indicate the interquartile range (IQR). Vertical lines and shading indicate the overall average across countries and 94% C.R., respectively. A) Belief, B) Support for Policy, C) Willingness to share climate-change information on social media, D) Number of trees planted in the WEPT task. Estimates shown in Tables S5-S8.

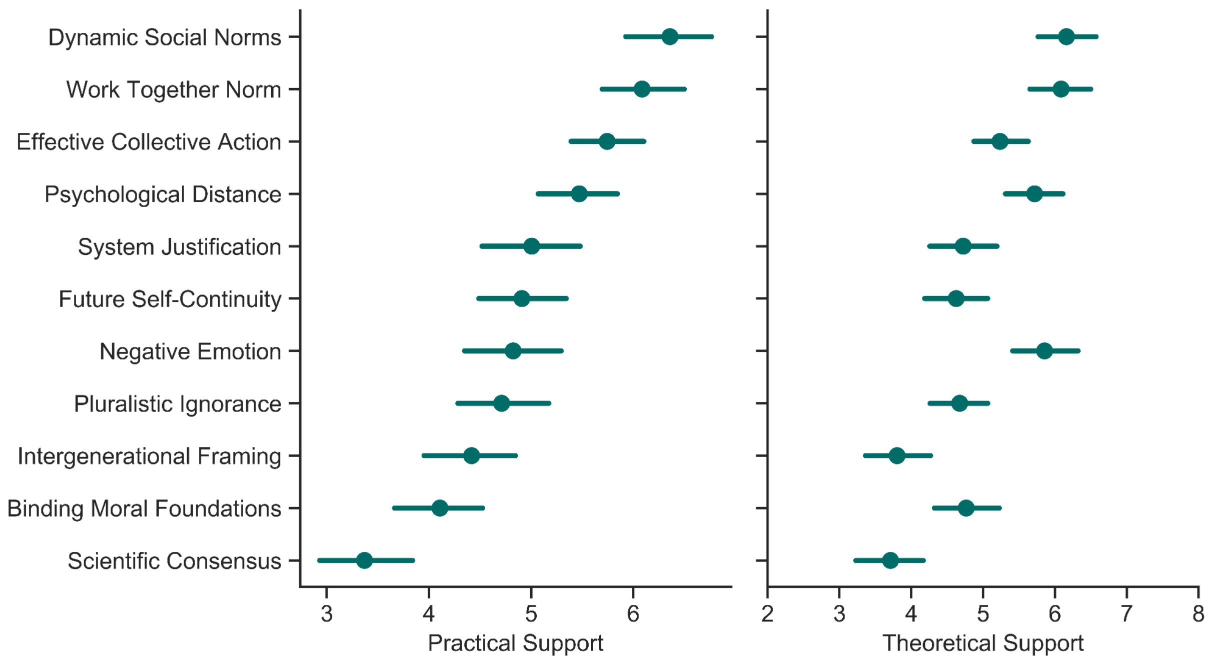

Figure S5. Average support of each crowdsourced intervention from a sample of 188 behavioral scientists (coauthors on the current paper) who were asked to rate the interventions on perceived efficiency (practical support) and theoretical value (theoretical support).

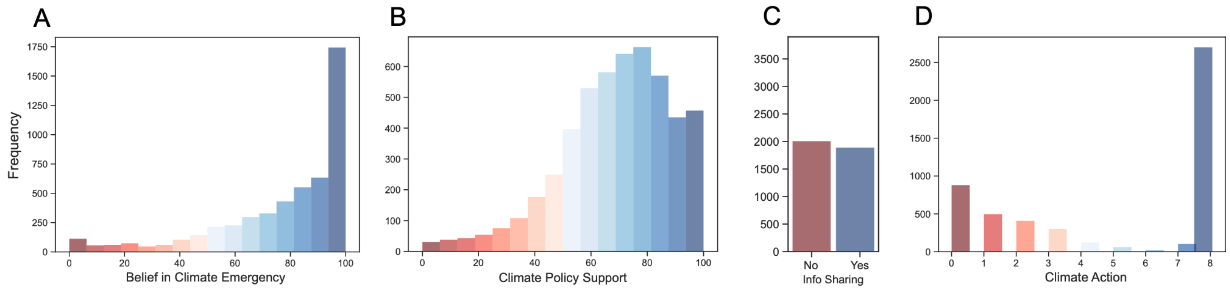

Figure S6. Frequency plots of A) belief, B) policy support, C) climate information sharing, and D) number of trees planted) in the control condition (N=5,086, from 63 countries), emphasizing the distributions of these dependent variables at baseline.

Table S1. Bayesian estimates of belief in climate change in each intervention, compared to the control condition.

Intervention	mean	sd	1.5%	3%	median	97%	98.5%
Psych Distance	2.255	0.332	1.524	1.619	2.263	2.865	2.954
Collective Action	1.454	0.338	0.712	0.816	1.457	2.07	2.177
Fut. Self Cont.	1.257	0.351	0.547	0.637	1.249	1.922	2.037
Letter Fut. Gen.	1.206	0.341	0.471	0.553	1.203	1.863	1.952
System Justif.	0.847	0.329	0.112	0.218	0.852	1.458	1.555
Sci. Consensus	0.426	0.345	-0.341	-0.252	0.437	1.052	1.134
Binding Moral	0.348	0.347	-0.385	-0.295	0.352	0.994	1.087
Dyn. Soc. Norm	0.343	0.342	-0.421	-0.324	0.35	0.969	1.073
Neg. Emotions	0.244	0.341	-0.488	-0.404	0.238	0.907	0.997
Plural Ignorance	-0.263	0.348	-0.976	-0.894	-0.274	0.404	0.507
Work Together Norm	-1.195	0.359	-1.947	-1.839	-1.198	-0.5	-0.374

Table S2. Bayesian estimates of policy support in each intervention, compared to the control condition.

Intervention	mean	sd	1.5%	3%	median	97%	98.5%
Letter Future Gen.	2.552	0.318	1.847	1.95	2.55	3.155	3.236
CollectAction	2.406	0.289	1.794	1.863	2.405	2.967	3.046
FutureSelfCont	2.111	0.308	1.464	1.545	2.111	2.696	2.804
PsychDistance	1.066	0.302	0.388	0.486	1.07	1.64	1.722
DynamicNorm	0.93	0.294	0.295	0.385	0.927	1.492	1.581
SystemJust	0.741	0.287	0.115	0.201	0.739	1.293	1.368
BindingMoral	0.511	0.298	-0.133	-0.051	0.506	1.062	1.159
SciConsens	0.471	0.309	-0.226	-0.098	0.468	1.041	1.135
NegativeEmotions	0.148	0.296	-0.501	-0.411	0.152	0.708	0.797
Work Together Norm	0.145	0.3	-0.485	-0.396	0.142	0.711	0.795
PluralIgnorance	0.096	0.299	-0.557	-0.463	0.094	0.666	0.737

Table S3. Bayesian estimates of sharing intentions in each intervention, compared to the control condition.

Intervention	mean	sd	1.5%	3%	median	97%	98.5%
Neg. Emotions	12.106	1.293	9.325	9.671	12.079	14.593	14.966
Letter Fut. Gen.	10.754	1.419	7.817	8.099	10.749	13.535	13.893
Collective Action	10.527	1.319	7.611	8.108	10.536	13.014	13.421
Psych Distance	9.085	1.338	6.288	6.631	9.074	11.611	11.974
Fut. Self Cont.	8.255	1.41	5.271	5.64	8.249	10.876	11.254
Dyn. Soc. Norm	7.978	1.317	5.085	5.465	7.982	10.455	10.847
Work Together Norm	7.535	1.331	4.739	5.111	7.515	10.078	10.395
System Justif.	5.812	1.304	2.966	3.367	5.801	8.301	8.639
Binding Moral	4.455	1.326	1.656	2.009	4.432	6.964	7.338
Sci. Consensus	4.444	1.352	1.527	1.851	4.449	6.964	7.388
Plural Ignorance	2.309	1.32	-0.51	-0.1	2.276	4.82	5.259

Table S4. Bayesian estimates of number of trees planted in each intervention, compared to the control condition.

Intervention	mean	sd	1.5%	3%	median	97%	98.5%
Binding Moral	0.038	0.082	-0.14	-0.117	0.039	0.192	0.213
Sci. Consensus	0.003	0.081	-0.17	-0.146	0.004	0.158	0.184
Dyn. Soc. Norm	-0.009	0.081	-0.182	-0.161	-0.008	0.144	0.171
System Justif.	-0.12	0.081	-0.295	-0.272	-0.12	0.031	0.057
Plural Ignorance	-0.165	0.081	-0.339	-0.321	-0.165	-0.014	0.008
Collective Action	-0.185	0.083	-0.361	-0.337	-0.187	-0.028	-0.005
Fut. Self Cont.	-0.229	0.086	-0.413	-0.391	-0.229	-0.061	-0.038
Letter Fut. Gen.	-0.365	0.087	-0.552	-0.526	-0.365	-0.199	-0.174
Work Together Norm	-0.438	0.08	-0.615	-0.593	-0.44	-0.283	-0.263
Psych Distance	-0.51	0.083	-0.689	-0.664	-0.509	-0.349	-0.326
Neg. Emotions	-0.536	0.082	-0.725	-0.695	-0.535	-0.377	-0.357

Table S5. Belief by country.

Country	mean	sd	1.5%	3%	median	97%	98.5%
Philippines	96.747	0.46	95.708	95.843	96.773	97.553	97.635
Portugal	94.055	0.451	93.031	93.157	94.072	94.89	94.99
Uganda	93.387	0.481	92.302	92.447	93.39	94.278	94.404
Ghana	92.957	0.489	91.872	92.014	92.963	93.867	93.989
Tanzania	92.854	1.084	90.229	90.67	92.915	94.733	94.991
Brazil	92.607	0.355	91.792	91.912	92.617	93.239	93.328
Turkey	92.478	0.447	91.522	91.629	92.477	93.293	93.402
Gambia	92.463	0.3	91.828	91.905	92.466	93.007	93.081
Chile	92.452	0.524	91.247	91.434	92.479	93.395	93.53
Serbia	92.398	0.642	90.878	91.134	92.411	93.626	93.816
Venezuela	91.975	1.179	89.143	89.564	92.049	94.006	94.291
Uruguay	91.697	0.578	90.342	90.559	91.723	92.707	92.883
Vietnam	91.631	0.676	90.067	90.339	91.654	92.847	93.026
Mexico	91.399	0.578	90.128	90.277	91.388	92.485	92.636
Italy	91.213	0.369	90.347	90.48	91.228	91.897	92.003
Kenya	91.167	0.698	89.535	89.759	91.208	92.367	92.525
North Macedonia	90.815	0.498	89.665	89.846	90.835	91.675	91.79
Peru	90.601	0.73	88.921	89.194	90.617	91.9	92.056
Ecuador	90.524	0.553	89.267	89.446	90.545	91.505	91.675
Nigeria	90.129	0.411	89.234	89.343	90.135	90.893	91.006
Czechia	89.293	0.7	87.628	87.889	89.314	90.554	90.792
Armenia	89.19	0.716	87.653	87.861	89.188	90.56	90.749
Canada	89.135	0.52	87.976	88.102	89.159	90.058	90.214
South Africa	89.102	0.767	87.409	87.612	89.127	90.537	90.681
India	88.96	0.664	87.432	87.654	88.98	90.168	90.389
Sri Lanka	88.652	0.865	86.66	86.929	88.682	90.198	90.408
Ukraine	88.368	0.759	86.643	86.881	88.406	89.702	89.894
Spain	88.212	0.781	86.348	86.653	88.233	89.699	89.897
Romania	88.046	0.883	86.064	86.301	88.058	89.647	89.865
Ireland	87.15	0.666	85.624	85.842	87.154	88.367	88.588
South Korea	85.666	0.812	83.785	84.024	85.699	87.144	87.398
France	85.492	0.592	84.076	84.292	85.506	86.551	86.707
Algeria	85.084	0.919	83.045	83.311	85.09	86.747	86.995
Morocco	84.872	0.971	82.576	82.881	84.926	86.581	86.805
China	84.692	0.709	83.101	83.32	84.711	85.955	86.16
Bulgaria	84.629	0.771	82.955	83.208	84.628	86.073	86.284
Switzerland	84.515	0.684	82.977	83.163	84.53	85.741	85.911
Thailand	83.984	0.967	81.835	82.115	84.022	85.761	85.979
Singapore	83.941	0.867	82.046	82.288	83.938	85.568	85.934
Poland	83.593	0.518	82.443	82.566	83.615	84.527	84.672

Germany	83.33	0.632	81.981	82.169	83.321	84.533	84.705
UK	82.663	0.608	81.265	81.516	82.674	83.764	83.941
Austria	82.254	1.04	79.734	80.151	82.305	84.075	84.398
UAE	81.942	1.016	79.602	79.966	81.958	83.751	84.045
Greece	81.318	1.051	78.973	79.264	81.332	83.301	83.531
Australia	81.316	0.82	79.469	79.7	81.345	82.823	83.037
Russia	81.226	0.708	79.681	79.887	81.235	82.584	82.728
Slovenia	80.135	1.18	77.379	77.743	80.189	82.23	82.445
Netherlands	80.092	0.677	78.589	78.784	80.099	81.354	81.533
Denmark	79.843	0.972	77.656	77.993	79.844	81.63	81.926
Finland	79.436	1.127	77.014	77.333	79.425	81.454	81.737
Slovakia	79.396	0.89	77.342	77.609	79.438	80.904	81.136
Belgium	79.384	0.875	77.393	77.659	79.424	80.966	81.165
Sweden	79.343	0.648	77.842	78.062	79.333	80.527	80.699
Taiwan	79.281	1.756	75.177	75.899	79.342	82.588	83.03
Sudan	79.217	1.058	76.913	77.229	79.241	81.058	81.214
New Zealand	79.152	0.859	77.212	77.488	79.169	80.748	80.977
Japan	79.148	0.733	77.501	77.759	79.147	80.443	80.629
Latvia	76.918	1.378	73.982	74.384	76.929	79.475	79.801
USA	76.861	0.467	75.819	75.945	76.882	77.687	77.8
Norway	76.248	0.898	74.234	74.541	76.256	77.931	78.188
Saudi Arabia	73.952	1.469	70.969	71.339	73.941	76.716	77.138
Israel	73.439	0.891	71.426	71.688	73.468	75.037	75.294

Table S6. Policy support by country.

Country	mean	sd	1.5%	3%	median	97%	98.5%
Turkey	80.201	0.635	78.839	79.014	80.185	81.407	81.573
Brazil	78.445	0.565	77.204	77.35	78.442	79.503	79.643
Chile	78.425	0.469	77.42	77.547	78.429	79.31	79.438
Uganda	78.278	0.893	76.328	76.582	78.272	79.967	80.232
India	77.921	0.647	76.479	76.687	77.926	79.164	79.342
Sri Lanka	77.858	0.767	76.13	76.388	77.849	79.3	79.52
Ghana	77.564	0.744	75.985	76.178	77.554	78.958	79.201
Taiwan	77.336	1.48	74.05	74.497	77.335	80.053	80.405
Ukraine	76.983	0.724	75.392	75.62	76.997	78.318	78.554
Uruguay	76.859	0.763	75.198	75.402	76.867	78.313	78.496
Nigeria	76.617	0.512	75.497	75.653	76.619	77.569	77.714
Venezuela	76.565	1.584	73.061	73.495	76.589	79.495	79.863
Mexico	76.361	0.827	74.582	74.852	76.365	77.92	78.152
Philippines	76.353	1.293	73.538	73.903	76.38	78.786	79.061
Vietnam	76.083	0.932	73.989	74.3	76.096	77.784	78.084
Gambia	75.981	0.793	74.187	74.467	75.989	77.488	77.73
China	75.82	0.649	74.416	74.624	75.808	77.069	77.271
Serbia	75.646	0.934	73.624	73.868	75.656	77.348	77.657
Portugal	75.578	0.809	73.839	74.051	75.566	77.121	77.359
Algeria	75.326	0.759	73.669	73.888	75.319	76.722	76.976
Spain	75.11	0.838	73.305	73.558	75.125	76.663	76.945
Sudan	75.01	0.809	73.256	73.441	75.021	76.491	76.666
Morocco	74.933	0.892	73.007	73.267	74.925	76.637	76.907
Ecuador	74.365	0.76	72.765	72.986	74.358	75.799	75.993
Bulgaria	73.86	0.764	72.147	72.436	73.864	75.284	75.522
Thailand	73.766	0.932	71.752	71.954	73.781	75.476	75.78
Italy	73.757	0.543	72.576	72.763	73.755	74.782	74.927
South Africa	73.328	0.895	71.409	71.653	73.328	75.024	75.341
Ireland	73.256	0.735	71.7	71.859	73.255	74.615	74.779
Kenya	73.196	0.885	71.283	71.53	73.205	74.859	75.06
UK	72.706	0.61	71.391	71.559	72.71	73.877	74.085
South Korea	72.512	0.829	70.713	70.914	72.52	74.064	74.302
Canada	72.018	0.661	70.594	70.774	72.007	73.262	73.445
Singapore	71.941	0.887	70.005	70.292	71.936	73.608	73.864
North Macedonia	71.941	0.652	70.468	70.75	71.963	73.132	73.365
Peru	71.87	0.93	69.824	70.114	71.865	73.592	73.83
Australia	71.744	0.748	70.123	70.312	71.731	73.187	73.399
Romania	71.679	0.983	69.539	69.809	71.701	73.531	73.792
Tanzania	71.283	1.955	66.959	67.596	71.282	74.866	75.397
France	70.641	0.612	69.278	69.475	70.646	71.785	71.944

Netherlands	70.631	0.586	69.356	69.554	70.639	71.729	71.892
UAE	70.519	0.928	68.478	68.759	70.536	72.248	72.512
Greece	70.466	0.803	68.725	68.978	70.471	71.986	72.194
Denmark	70.356	0.84	68.5	68.761	70.359	71.915	72.177
Poland	70.223	0.509	69.155	69.301	70.212	71.199	71.354
Armenia	69.95	0.812	68.195	68.479	69.932	71.495	71.768
Switzerland	69.881	0.725	68.28	68.481	69.878	71.207	71.431
Slovenia	69.713	0.896	67.822	68.03	69.709	71.384	71.599
Czechia	68.975	0.906	66.989	67.269	68.965	70.681	70.886
Israel	68.435	0.591	67.119	67.298	68.437	69.543	69.756
Austria	68.046	0.949	66.023	66.281	68.058	69.777	70.017
USA	67.88	0.431	66.916	67.036	67.887	68.671	68.771
Germany	67.674	0.643	66.299	66.474	67.67	68.908	69.099
Belgium	67.118	0.746	65.512	65.722	67.098	68.528	68.735
New Zealand	67.028	0.767	65.367	65.599	67.027	68.481	68.697
Norway	67.013	0.758	65.327	65.539	67.009	68.436	68.66
Sweden	66.273	0.58	64.976	65.172	66.268	67.352	67.507
Russia	64.992	0.579	63.756	63.92	64.986	66.103	66.259
Finland	64.545	0.994	62.353	62.61	64.544	66.362	66.646
Saudi Arabia	64.444	1.093	62.171	62.508	64.416	66.544	66.834
Slovakia	64.362	0.703	62.865	63.038	64.358	65.689	65.858
Latvia	62.491	0.983	60.326	60.591	62.512	64.358	64.592
Japan	58.939	0.616	57.613	57.798	58.945	60.097	60.275

Table S7. Sharing intentions by country.

Country	mean	sd	1.5%	3%	median	97%	98.5%
Kenya	93.31	1.437	89.913	90.418	93.426	95.709	95.969
Uganda	91.743	1.88	87.214	87.855	91.873	94.834	95.339
Mexico	90.518	1.53	86.866	87.42	90.596	93.149	93.489
Taiwan	88.544	2.757	81.7	83.04	88.705	93.337	94.025
Ecuador	88.295	1.408	85.068	85.514	88.361	90.728	91.051
Gambia	87.53	1.656	83.911	84.365	87.581	90.524	91.035
Nigeria	86.151	0.977	83.916	84.251	86.166	87.89	88.244
Ghana	85.086	1.758	81.183	81.675	85.133	88.257	88.665
Tanzania	82.466	4.43	72.229	73.671	82.664	90.198	90.939
UAE	81.872	1.717	78.087	78.663	81.876	84.983	85.388
Vietnam	81.416	2.309	76.107	76.954	81.581	85.437	86.051
Thailand	81.093	2.097	76.417	77.093	81.121	84.968	85.517
China	80.925	1.44	77.75	78.191	80.932	83.51	83.837
Peru	80.692	2.314	75.356	76.058	80.749	84.931	85.465
Saudi Arabia	80.387	1.778	76.361	76.968	80.417	83.59	84.102
South Korea	79.702	2.197	74.722	75.38	79.756	83.727	84.351
India	78.964	1.608	75.443	75.878	78.991	81.939	82.332
South Africa	77.534	2.145	72.813	73.381	77.549	81.466	82.084
Morocco	76.654	2.116	71.898	72.58	76.713	80.525	81.113
Chile	74.184	1.191	71.658	71.97	74.167	76.464	76.76
Brazil	73.233	1.409	70.123	70.521	73.256	75.824	76.273
Algeria	71.205	2.15	66.353	67.162	71.19	75.038	75.525
Singapore	68.836	2.176	64.203	64.819	68.883	72.738	73.444
Uruguay	68.78	2.526	63.148	63.917	68.883	73.361	74.062
Greece	66.537	2.305	61.533	62.161	66.559	70.846	71.454
Sudan	66.491	1.941	62.435	62.844	66.5	70.158	70.738
Venezuela	66.344	4.934	55.454	56.782	66.413	75.446	77.046
Philippines	65.902	4.414	56.219	57.384	65.891	73.895	75.357
France	64.752	1.5	61.54	61.94	64.755	67.583	67.945
Sri Lanka	64.328	2.918	57.922	58.69	64.353	69.722	70.551
Bulgaria	64.26	2.122	59.538	60.124	64.339	68.201	68.753
Ireland	62.759	2.204	57.926	58.503	62.775	66.783	67.301
USA	61.391	0.682	59.916	60.119	61.385	62.695	62.902
Italy	57.09	1.491	53.891	54.306	57.102	59.856	60.285
UK	55.063	1.393	52.023	52.497	55.092	57.584	57.986
Spain	54.985	3.029	48.591	49.382	54.984	60.563	61.501
Slovenia	53.929	2.686	48.062	48.817	53.924	59.043	59.99
Sweden	53.058	1.234	50.478	50.752	53.076	55.32	55.776
Denmark	51.981	2.146	47.428	47.898	51.99	56.016	56.542
Turkey	48.186	2.195	43.447	44.117	48.156	52.302	52.844

Australia	45.53	2.075	40.871	41.597	45.541	49.522	50.215
New Zealand	37.913	1.782	33.92	34.598	37.917	41.228	41.754
Portugal	36.846	2.624	31.254	32.018	36.884	41.748	42.542
Finland	35.997	2.217	31.283	31.857	35.971	40.224	40.93
Canada	35.824	1.684	32.27	32.678	35.782	38.918	39.367
Poland	35.555	1.239	32.906	33.248	35.562	37.891	38.317
Belgium	35.172	1.781	31.455	31.861	35.137	38.561	39.07
Ukraine	34.285	2.412	29.372	29.887	34.258	38.955	39.714
Armenia	32.677	2.393	27.546	28.264	32.635	37.313	37.996
Germany	31.981	1.466	28.809	29.274	31.954	34.732	35.24
Israel	31.629	1.68	28.09	28.442	31.617	34.834	35.395
Slovakia	30.655	1.647	27.065	27.637	30.641	33.806	34.307
North Macedonia	28.421	1.871	24.443	24.903	28.461	31.937	32.364
Austria	27.791	2.325	22.971	23.578	27.753	32.242	32.957
Switzerland	26.868	1.743	23.171	23.71	26.854	30.263	30.85
Serbia	26.537	2.713	21.029	21.639	26.433	31.747	32.44
Russia	26.052	1.41	23.027	23.445	26.03	28.729	29.216
Japan	24.205	1.415	21.274	21.618	24.199	26.888	27.234
Czechia	20.411	1.909	16.319	16.887	20.369	24.17	24.672
Romania	19.597	2.24	15.141	15.559	19.52	24.07	24.782
Netherlands	19.335	1.113	17.006	17.313	19.325	21.478	21.761
Norway	19.178	1.467	16.118	16.46	19.168	22.081	22.577
Latvia	17.684	1.9	13.816	14.27	17.629	21.378	22.103

Table S8. Number of trees planted by country.

Country	mean	sd	1.5%	3%	median	97%	98.5%
Kenya	6.958	0.42	6.048	6.167	6.978	7.678	7.745
Serbia	6.851	0.346	6.188	6.268	6.824	7.55	7.636
Venezuela	6.815	0.485	5.819	5.939	6.796	7.734	7.811
Philippines	6.447	0.459	5.606	5.712	6.393	7.52	7.676
Chile	6.418	0.09	6.222	6.245	6.418	6.583	6.613
Slovakia	6.348	0.108	6.098	6.14	6.349	6.549	6.585
Italy	6.33	0.129	6.062	6.101	6.327	6.582	6.616
China	6.204	0.161	5.878	5.917	6.198	6.525	6.587
UAE	6.126	0.145	5.817	5.853	6.126	6.4	6.435
South Korea	6.126	0.177	5.761	5.808	6.122	6.481	6.55
Thailand	6.085	0.16	5.744	5.789	6.088	6.385	6.438
Poland	6.057	0.098	5.853	5.878	6.057	6.239	6.27
Saudi Arabia	5.959	0.173	5.584	5.635	5.96	6.288	6.344
Norway	5.894	0.121	5.629	5.662	5.895	6.125	6.15
Spain	5.855	0.173	5.486	5.529	5.855	6.184	6.24
Australia	5.807	0.12	5.53	5.576	5.81	6.023	6.054
Nigeria	5.776	0.106	5.545	5.575	5.776	5.972	6.002
Czechia	5.75	0.209	5.329	5.372	5.745	6.167	6.23
Romania	5.674	0.194	5.263	5.322	5.67	6.046	6.1
Mexico	5.659	0.17	5.296	5.343	5.657	5.981	6.03
Turkey	5.607	0.161	5.266	5.312	5.602	5.918	5.965
Brazil	5.591	0.114	5.339	5.375	5.591	5.798	5.832
Uganda	5.576	0.239	5.116	5.164	5.565	6.052	6.154
Latvia	5.47	0.308	4.884	4.948	5.45	6.08	6.183
France	5.449	0.104	5.221	5.25	5.451	5.639	5.668
Portugal	5.446	0.28	4.913	4.979	5.427	6.023	6.137
Ukraine	5.369	0.247	4.878	4.938	5.356	5.874	5.977
Uruguay	5.369	0.172	5.005	5.047	5.368	5.691	5.743
Greece	5.368	0.152	5.041	5.084	5.367	5.649	5.696
Bulgaria	5.365	0.141	5.065	5.102	5.362	5.634	5.68
Switzerland	5.359	0.132	5.067	5.112	5.356	5.615	5.658
Ghana	5.348	0.171	4.976	5.022	5.35	5.679	5.735
New Zealand	5.34	0.129	5.062	5.096	5.341	5.58	5.613
Belgium	5.317	0.123	5.05	5.083	5.316	5.555	5.586
Japan	5.296	0.108	5.059	5.094	5.295	5.5	5.523
Denmark	5.189	0.134	4.897	4.938	5.19	5.442	5.483
Vietnam	5.137	0.222	4.669	4.729	5.131	5.561	5.619
Canada	5.121	0.132	4.832	4.87	5.118	5.372	5.414
Israel	5.102	0.127	4.831	4.867	5.103	5.337	5.376
USA	5.097	0.065	4.953	4.978	5.096	5.22	5.239

South Africa	5.096	0.169	4.726	4.77	5.101	5.411	5.449
Peru	5.083	0.212	4.623	4.691	5.082	5.493	5.557
UK	5.034	0.103	4.813	4.839	5.035	5.225	5.253
Sri Lanka	4.928	0.19	4.519	4.566	4.931	5.282	5.334
Germany	4.919	0.104	4.694	4.725	4.918	5.115	5.139
Russia	4.893	0.119	4.635	4.669	4.892	5.119	5.16
Ecuador	4.887	0.163	4.541	4.585	4.885	5.197	5.24
Algeria	4.772	0.167	4.417	4.456	4.773	5.086	5.134
Tanzania	4.68	0.387	3.862	3.969	4.675	5.421	5.561
Netherlands	4.567	0.107	4.332	4.363	4.565	4.776	4.806
Morocco	4.557	0.178	4.177	4.224	4.558	4.896	4.951
Sweden	4.441	0.093	4.233	4.265	4.442	4.609	4.641
North Macedonia	4.262	0.146	3.961	3.991	4.259	4.539	4.584
Singapore	4.25	0.172	3.875	3.929	4.25	4.567	4.616
Austria	4.204	0.172	3.828	3.88	4.201	4.536	4.575
Gambia	4.179	0.173	3.806	3.852	4.181	4.503	4.562
Sudan	4.128	0.152	3.804	3.843	4.126	4.418	4.462
Slovenia	3.918	0.175	3.536	3.593	3.915	4.251	4.299
Finland	3.843	0.156	3.507	3.545	3.844	4.133	4.177
Armenia	3.792	0.176	3.419	3.466	3.79	4.13	4.174
Ireland	3.246	0.145	2.932	2.979	3.24	3.526	3.561
India	2.921	0.143	2.631	2.667	2.918	3.199	3.233
Taiwan	1.469	0.184	1.107	1.153	1.459	1.836	1.908

Table S9: Coefficient table from pre-registered analysis of climate beliefs. Results are from a linear mixed effects model with climate beliefs as the dependent variable, condition as the fixed effect, including item (4 beliefs), participant, and country as random effects. Estimates are shown relative to the Control Condition.

Intervention	Estimate	SE	*df*	*t*	*d*	*p*
(Intercept)	79.98	0.88	79.30	91.20	20.48	**< .001**
PsychDistance	3.22	0.47	59166.56	6.86	0.06	**< .001**
CollectAction	2.25	0.46	59166.10	4.90	0.04	**< .001**
LetterFutureGen	1.88	0.49	59170.10	3.84	0.03	**< .001**
SystemJust	1.71	0.46	59170.14	3.74	0.03	**< .001**
FutureSelfCont	1.80	0.48	59176.06	3.72	0.03	**< .001**
SciConsens	1.25	0.46	59168.87	2.75	0.02	**0.006**
BindingMoral	1.09	0.46	59172.21	2.37	0.02	**0.018**
PluralIgnorance	0.93	0.46	59161.92	2.03	0.02	**0.042**
DynamicNorm	0.76	0.46	59185.00	1.66	0.01	0.098
NegativeEmotions	0.75	0.46	59166.90	1.63	0.01	0.103
WorkTogetherNorm	-0.62	0.46	59160.72	-1.36	-0.01	0.174

Table S10: Coefficient table from pre-registered analysis of climate policy support. Results are from a linear mixed effects model with climate policy support, as the dependent variable, condition as the fixed effect, including item (9 policies), participant, and country as random effects. Estimates are shown relative to the Control Condition.

Intervention	Estimate	SE	*df*	*t*	*d*	*p*
(Intercept)	70.23	4.02	8.42	17.45	12.03	**< .001**
CollectAction	2.89	0.38	58566.33	7.71	0.06	**< .001**
LetterFutureGen	2.81	0.40	58603.94	7.01	0.06	**< .001**
FutureSelfCont	2.06	0.40	58598.68	5.21	0.04	**< .001**
PsychDistance	1.34	0.38	58643.56	3.49	0.03	**< .001**
DynamicNorm	1.14	0.38	58602.04	3.04	0.03	**0.002**
SystemJust	0.91	0.37	58568.86	2.44	0.02	**0.015**
SciConsens	0.80	0.37	58609.08	2.14	0.02	**0.032**
BindingMoral	0.72	0.38	58582.48	1.91	0.02	0.057
PluralIgnorance	0.33	0.37	58578.83	0.89	0.01	0.373
WorkTogetherNorm	-0.10	0.38	58621.02	-0.26	0.00	0.794
NegativeEmotions	-0.25	0.38	58576.15	-0.68	-0.01	0.499

Table S11: Coefficient table from pre-registered analysis of Social Media Sharing. Results are from logistic mixed effects model with social media sharing as the dependent variable, condition as the fixed effect, including country as random effects. Estimates are shown relative to Control.

Intervention	Estimate	SE	*z*	*d*	*p*
(Intercept)	0.08	0.15	0.51	0.04	0.611
NegativeEmotions	0.49	0.05	9.43	0.27	**< .001**
CollectAction	0.40	0.05	7.76	0.22	**< .001**
LetterFutureGen	0.40	0.06	7.24	0.22	**< .001**
PsychDistance	0.35	0.05	6.64	0.19	**< .001**
DynamicNorm	0.31	0.05	6.12	0.17	**< .001**
FutureSelfCont	0.31	0.05	5.82	0.17	**< .001**
WorkTogetherNorm	0.23	0.05	4.65	0.13	**< .001**
SystemJust	0.23	0.05	4.60	0.13	**< .001**
BindingMoral	0.19	0.05	3.81	0.11	**< .001**
SciConsens	0.18	0.05	3.65	0.10	**< .001**
PluralIgnorance	0.10	0.05	1.90	0.05	0.057

Table S12: Coefficient table from pre-registered analysis of WEPT. Results are from an ordinal mixed effects model with climate action (WEPT), as the dependent variable, condition as the fixed effect, including country as random effects. Estimates are shown relative to the Control Condition.

Intervention	Estimate	SE	*z*	*d*	*p*
BindingMoral	0.04	0.04	0.89	0.03	0.375
SciConsens	0.03	0.04	0.65	-0.01	0.513
DynamicNorm	0.01	0.04	0.25	-0.01	0.800
SystemJust	-0.05	0.04	-1.39	-0.05	0.163
PluralIgnorance	-0.07	0.04	-1.82	-0.05	0.068
CollectAction	-0.11	0.04	-3.02	-0.06	**0.003**
FutureSelfCont	-0.12	0.04	-3.04	-0.06	**0.002**
LetterFutureGen	-0.23	0.04	-5.67	-0.13	**< 0.001**
WorkTogetherNorm	-0.25	0.04	-6.61	-0.15	**< 0.001**
PsychDistance	-0.27	0.04	-7.11	-0.15	**< 0.001**
NegativeEmotions	-0.29	0.04	-7.67	-0.16	**< 0.001**

Table S13: Coefficient table for an ordinal mixed effects model with climate action (i.e., number of trees planted in the WEPT) as the dependent variable, belief in climate change as the fixed effect, including country random effects.

Predictor	Estimate	SE	*z*	*p*
Belief	0.01	0.0003	29.84	**< .001**

Table S14: Coefficient table for an ordinal mixed effects model with climate action (i.e., number of trees planted in the WEPT) as the dependent variable, policy support as the fixed effect, including country random effects.

Predictor	Estimate	SE	*z*	*p*
Policy	0.01	0.0004	30.72	**< .001**

Table S15: Coefficient table for an ordinal mixed effects model with climate action (i.e., number of trees planted in the WEPT) as the dependent variable, willingness to share climate information as the fixed effect, including country random effects.

Predictor	Estimate	SE	*z*	*p*
Willingness to share	0.33	0.02	16.29	**< .001**

Table S16: Coefficient table for an ordinal mixed effects model with climate action (i.e., number of trees planted in the WEPT) as the dependent variable, belief in climate change in each condition as the fixed effect, including country random effects.

Belief:Intervention	Estimate	SE	*z*	*p*
Belief:SciConsens	0.012	0.0005	24.96	**< 0.001**
Belief:BindingMoral	0.012	0.0005	24.77	**< 0.001**
Belief:DynamicNorm	0.011	0.0005	24.30	**< 0.001**
Belief:Control	0.011	0.0005	23.93	**< 0.001**
Belief:SystemJust	0.011	0.0005	22.72	**< 0.001**
Belief:PluralIgnorance	0.011	0.0005	22.40	**< 0.001**
Belief:CollectAction	0.010	0.0005	21.46	**< 0.001**
Belief:FutureSelfCont	0.010	0.0005	20.71	**< 0.001**
Belief:WorkTogetherNorm	0.009	0.0005	19.21	**< 0.001**
Belief:NegativeEmotions	0.008	0.0005	17.97	**< 0.001**
Belief:LetterFutureGen	0.009	0.0005	17.85	**< 0.001**
Belief:PsychDistance	0.008	0.0005	17.40	**< 0.001**

Table S17: Coefficient table for an ordinal mixed effects model with climate action (i.e., number of trees planted in the WEPT) as the dependent variable, policy support in each condition as the fixed effect, including country random effects.

Policy:Intervention	Estimate	SE	*z*	*p*
Policy:SciConsens	0.015	0.0006	26.760	< **0.001**
Policy:BindingMoral	0.015	0.0006	26.580	< **0.001**
Policy:DynamicNorm	0.015	0.0006	25.980	< **0.001**
Policy:Control	0.015	0.0006	25.850	< **0.001**
Policy:SystemJust	0.014	0.0006	24.650	< **0.001**
Policy:PluralIgnorance	0.014	0.0006	24.270	< **0.001**
Policy:CollectAction	0.013	0.0005	23.550	< **0.001**
Policy:FutureSelfCont	0.013	0.0006	22.370	< **0.001**
Policy:WorkTogetherNorm	0.012	0.0006	20.590	< **0.001**
Policy:LetterFutureGen	0.011	0.0006	20.000	< **0.001**
Policy:NegativeEmotions	0.011	0.0006	19.880	< **0.001**
Policy:PsychDistance	0.011	0.0006	19.200	< **0.001**

Table S18: Coefficient table for an ordinal mixed effects model with climate action (i.e., number of trees planted in the WEPT) as the dependent variable, willingness to share information in each condition as the fixed effect, including country random effects.

Sharing:Intervention	Estimate	SE	*z-value*	*p*
Share:DynamicNorm	0.471	0.0454	10.390	< **0.001**
Share:BindingMoral	0.466	0.0460	10.133	< **0.001**
Share:SciConsens	0.422	0.0454	9.296	< **0.001**
Share:Control	0.439	0.0475	9.242	< **0.001**
Share:CollectAction	0.340	0.0442	7.678	< **0.001**
Share:PluralIgnorance	0.357	0.0466	7.664	< **0.001**
Share:SystemJust	0.326	0.0452	7.211	< **0.001**
Share:FutureSelfCont	0.341	0.0493	6.913	< **0.001**
Share:LetterFutureGen	0.243	0.0482	5.037	< **0.001**
Share:WorkTogetherNorm	0.218	0.0438	4.976	< **0.001**
Share:PsychDistance	0.158	0.0459	3.438	< **0.001**
Share:NegativeEmotions	0.139	0.0430	3.239	**0.001**

Table S19: Coefficient table from analysis of belief. Results are from a linear mixed effects model with climate beliefs as the dependent variable, condition as the fixed effect, along with total condition time as a covariate, including item (4 beliefs), participant, and country as random effects. Estimates are shown relative to the Control Condition.

Intervention	Estimate	SE	*df*	*t*	*p*
(Intercept)	79.63	0.88	80.05	90.83	**< .001**
Condition Time	0.001	0.0002	59162.38	5.75	**< .001**
PsychDistance	3.08	0.47	59165.59	6.55	**< .001**
CollectAction	2.30	0.46	59165.43	5.01	**< .001**
SystemJust	1.90	0.46	59169.27	4.13	**< .001**
SciConsens	1.56	0.46	59168.19	3.40	**< .001**
FutureSelfCont	1.64	0.48	59175.38	3.39	**< .001**
LetterFutureGen	1.60	0.49	59169.22	3.26	**0.001**
BindingMoral	1.43	0.46	59171.14	3.08	**0.002**
PluralIgnorance	1.18	0.46	59160.52	2.56	**0.010**
DynamicNorm	1.00	0.46	59183.66	2.17	**0.030**
NegativeEmotions	0.73	0.46	59166.27	1.58	0.114
WorkTogetherNorm	-0.55	0.46	59159.98	-1.21	0.227

Table S20: Coefficient table from analysis of policy support. Results are from a linear mixed effects model with climate policy support, as the dependent variable, condition as the fixed effect, along with total condition time as a covariate, including item (9 policies), participant, and country as random effects. Estimates are shown relative to the Control Condition.

Intervention	Estimate	SE	*df*	*t*	*p*
(Intercept)	70.00	4.02	8.54	17.40	**< .001**
Condition Time	0.0008	0.0002	58259.82	4.64	**< .001**
CollectAction	2.92	0.37	58565.25	7.80	**< .001**
LetterFutureGen	2.62	0.40	58598.20	6.52	**< .001**
FutureSelfCont	1.96	0.40	58596.07	4.94	**< .001**
DynamicNorm	1.30	0.38	58596.74	3.45	**< .001**
PsychDistance	1.24	0.38	58642.02	3.24	**0.001**
SystemJust	1.04	0.38	58566.00	2.76	**0.006**
SciConsens	1.00	0.38	58602.11	2.67	**0.008**
BindingMoral	0.94	0.38	58574.93	2.48	**0.013**
PluralIgnorance	0.50	0.38	58573.00	1.32	0.188
WorkTogetherNorm	-0.05	0.37	58620.33	-0.14	0.890
NegativeEmotions	-0.27	0.37	58575.42	-0.72	0.474

Table S21: Coefficient table from analysis of Social Media Sharing. Results are from logistic mixed effects model with social media sharing as the dependent variable, condition as the fixed effect, along with total condition time as a covariate, including country as random effects. Estimates are shown relative to Control.

Intervention	Estimate	SE	*z*	*p*
(Intercept)	0.07	0.15	0.50	0.620
Condition Time	0.000007	0.00003	0.24	0.812
NegativeEmotions	0.48	0.05	9.43	**< .001**
CollectAction	0.40	0.05	7.76	**< .001**
LetterFutureGen	0.39	0.05	7.17	**< .001**
PsychDistance	0.35	0.05	6.61	**< .001**
DynamicNorm	0.31	0.05	6.11	**< .001**
FutureSelfCont	0.31	0.05	5.79	**< .001**
WorkTogetherNorm	0.23	0.05	4.66	**< .001**
SystemJust	0.23	0.05	4.61	**< .001**
BindingMoral	0.19	0.05	3.80	**< .001**
SciConsens	0.18	0.05	3.65	**< .001**
PluralIgnorance	0.10	0.05	1.92	0.055

Table S22: Coefficient table from analysis of WEPT. Results are from an ordinal mixed effects model with climate action (WEPT), as the dependent variable, condition as the fixed effect, along with intervention time as a covariate, including country as random effects. Estimates are shown relative to the Control Condition.

Intervention	Estimate	SE	*z*	*p*
Condition Time	0.001	0.000	18.88	**< .001**
BindingMoral	0.27	0.04	6.20	**< .001**
SciConsens	0.25	0.04	5.67	**< .001**
DynamicNorm	0.19	0.04	4.35	**< .001**
PluralIgnorance	0.12	0.04	2.86	**0.004**
SystemJust	0.09	0.04	2.13	**0.033**
CollectAction	-0.06	0.04	-1.52	0.129
WorkTogetherNorm	-0.18	0.04	-4.30	**< .001**
FutureSelfCont	-0.19	0.04	-4.31	**< .001**
NegativeEmotions	-0.29	0.04	-7.01	**< .001**
PsychDistance	-0.34	0.04	-8.30	**< .001**
LetterFutureGen	-0.38	0.04	-8.79	**< .001**

Table S23: Coefficient table from analysis of WEPT. Results are from an ordinal mixed effects model with climate action (WEPT), as the dependent variable, condition by condition time interaction as fixed effects, including country as random effects. Estimates are shown relative to the Control Condition.

Fixed Effect	Estimate	SE	*z*	*p*
Condition Time	0.002	0.000	8.572	**< .001**
SciConsens	0.448	0.076	5.892	**< .001**
DynamicNorm	0.418	0.077	5.447	**< .001**
PluralIgnorance	0.396	0.075	5.248	**< .001**
SystemJust	0.364	0.077	4.732	**< .001**
CollectAction	0.192	0.079	2.442	**0.015**
WorkTogetherNorm	0.179	0.079	2.269	**0.023**
FutureSelfCont	0.151	0.081	1.870	**0.061**
NegativeEmotions	0.050	0.079	0.626	.531
LetterFutureGen	-0.029	0.085	-0.341	.733
PsychDistance	-0.104	0.083	-1.262	.207
BindingMoral	-0.646	0.076	-8.501	**< .001**
BindingMoral:Condition Time	0.753	0.021	35.598	**< .001**
SciConsens:Condition Time	0.003	0.001	2.260	**.024**
DynamicNorm:Condition Time	-0.001	0.000	-1.269	.204
PluralIgnorance:Condition Time	-0.001	0.000	-2.562	**.010**
SystemJust:Condition Time	-0.001	0.000	-3.572	**< .001**
CollectAction:Condition Time	-0.001	0.000	-3.800	**< .001**
PsychDistance:Condition Time	-0.001	0.000	-4.072	**< .001**

LetterFutureGen:Condition Time	-0.001	0.000	-5.235	**< .001**
NegativeEmotions:Condition Time	-0.001	0.000	-5.246	**< .001**
FutureSelfCont:Condition Time	-0.001	0.000	-5.254	**< .001**
WorkTogetherNorm:Condition Time	-0.002	0.000	-5.594	**< .001**

Table S24: Coefficient table from analysis of WEPT. Results are from an ordinal mixed effects model with climate action (WEPT) as the dependent variable (coded as completed numbers of pages scored at least as 80% accurate), condition as the fixed effect, including country as random effects. Estimates are shown relative to the Control Condition.

Intervention	Estimate	SE	*z*	*p*
BindingMoral	0.03	0.04	0.89	0.375
SciConsens	0.02	0.04	0.65	0.513
DynamicNorm	0.01	0.04	0.25	0.800
SystemJust	-0.05	0.04	-1.39	0.163
PluralIgnorance	-0.07	0.04	-1.82	0.068
CollectAction	-0.11	0.04	-3.02	**0.003**
FutureSelfCont	-0.12	0.04	-3.04	**0.002**
LetterFutureGen	-0.23	0.04	-5.67	**< .001**
WorkTogetherNorm	-0.25	0.04	-6.61	**< .001**
PsychDistance	-0.27	0.04	-7.11	**< .001**
NegativeEmotions	-0.29	0.04	-7.67	**< .001**

Table S25: To test whether there was a main effect of condition (for each outcome variable), we conducted a Wald test for each outcome. The Wald test evaluated the null hypothesis that the joint distribution of the estimated coefficients for all intervention conditions was the same as the estimated coefficient for the control condition. The p-values below 0.001 for all tested outcomes indicate a significant divergence of the joint distribution of estimated coefficients from that of the control, suggesting that the interventions had varying effects.

Outcome	W - statistics	df	*p*
Belief	160.99	11	**< 0.001**
Policy Support	105.10	11	**< 0.001**
Social Media Sharing	154.26	11	**< 0.001**
WEPT	227.89	11	**< 0.001**

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