



Net0Pathways through impRoved IAMs across Sectors, diMensions, and scAles

Publication with the results of the citizens' survey:

*Acceptance of highly uncertain climate
change mitigation measures by
informed European citizens:
implications for modeling*

Deliverable D1.3
26 August 2025



This project has received funding from the European Union's Horizon Europe programme under grant agreement No 101081604 and from the Swiss State Secretariat for Education, Research, and Innovation (SEFRI) (project number 101081604). Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Climate, Infrastructure and Environment Executive Agency (CINEA). Neither authority can be held responsible for them.

Deliverable Title	Publication with the results of the citizens' survey
Deliverable number	D1.3
Brief Description	The study measures informed acceptance, support, affect, and perceived feasibility-related uncertainties towards four mitigation measures (afforestation/reforestation, green hydrogen, bioenergy with carbon capture and storage, and a shift towards sustainable diets) of European citizens in Spain, Italy, Germany, France, Poland, and the Netherlands.
WP number	WP 1
Lead Beneficiary	UNIGE
Author(s)	Valeria Sorgato (UNIGE), Morris Krainz (UNIGE), Tobias Brosch (UNIGE), Evelina Trutnevyte (UNIGE)
Internal reviewer(s)	Johannes Emmerling (CMCC)
Deliverable Due Date	31 August 2025
Actual Delivery Date	26 August 2025
Nature of the Deliverable	R – Document, report
Dissemination Level	PU- Public
Keywords	acceptance, uncertainty, feasibility, carbon dioxide removal, climate change mitigation, informed citizens, integrated assessment models

Date	Vers.	Contributors	Pages
26 August 2025	1	Valeria Sorgato (UNIGE), Morris Krainz (UNIGE), Tobias Brosch (UNIGE), Evelina Trutnevyte (UNIGE)	81



Executive summary

Integrated Assessment Models (IAMs) are key tools for helping policymakers navigate the trade-offs of different climate change mitigation measures. However, IAMs frequently overlook public acceptance, even though not all mitigation measures are equally accepted and successful implementation ultimately depends on societal acceptance. Eliciting informed views on climate mitigation measures offers a more reliable guide to public acceptance because it captures preferences aligned with core values, giving modelers the more reliable social acceptance data they need to design socially viable mitigation pathways to inform policies. Yet, most research either captures initial impressions or informs participants about potential benefits or impacts, while overlooking the crucial role of uncertainty. Uncertainties surrounding the effectiveness of a measure to mitigate climate change may impact support for its implementation.

This study provides participants with information about the inherent uncertainties surrounding the mitigation potential and feasibility dimensions (technical, social, economic, and geophysical) of four key climate change mitigation measures (BECCS, afforestation/reforestation, green hydrogen, and sustainable diets) across the six highest-emitting European countries (Germany, France, Italy, Spain, Poland, and the Netherlands). This allows, first, to establish a more realistic picture of public acceptance and affect for these measures, and then to identify how perceived uncertainty and other key factors – such as trust, climate change beliefs, and knowledge – drive these informed views. In doing so, the study provides crucial insights for modelers seeking to develop more socially realistic mitigation pathways, and offers guidance for policymakers by identifying key drivers that influence public acceptance and affect, which is essential for improving the design and communication of climate policy.

The findings of this study show that providing uncertainty information decreases acceptance and, to a lower degree, affect towards the mitigation measures. Despite the negative effect of information, all measures, on average, remain positively evaluated, and differences between measures and countries remain stable. Afforestation/reforestation and green hydrogen are the most favoured, while BECCS and sustainable diets are the least. Significant differences across countries emerge, with Polish and Dutch participants showing lower acceptance and affect levels, and Spanish participants showing higher levels. Delving deeper, we identify the key drivers of these attitudes. Higher perceived uncertainty, particularly regarding a measure's technical and social feasibility, is the strongest predictor of opposition and negative feelings – an effect that was magnified when providing information, particularly for perceived social uncertainty. Conversely, strong climate change beliefs emerged as the most powerful driver of support and positive affect, followed by trust in climate scientists and subjective knowledge. Political trust and socio-demographic factors, by contrast, had limited influence.

This study makes several significant contributions. First, it establishes that eliciting public opinion after providing information on uncertainties yields a more realistic assessment of

public acceptance and affect levels, bringing citizen uncertainty perceptions closer to expert assessments and closing knowledge gaps. Second, the significant differences in acceptance and affect between measures and across countries provide crucial, empirically grounded insights for modelers for creating socially viable mitigation pathways and for policymakers for designing targeted, effective climate policy. Third, it highlights a notable resilience in public support: despite a decrease following the provision of uncertainty information, overall acceptance remains positive. We suggest this resilience is likely due to two factors: core positive feelings (affect) are impacted less significantly than acceptance, and strong climate change beliefs may act as a buffer. Finally, we pinpoint that public opposition is most strongly linked to perceived technical and social uncertainties, suggesting that for mitigation policies to succeed, they must be communicated and framed as both technologically sound and socially viable.



Acceptance of highly uncertain climate change mitigation measures by informed European citizens: implications for modeling

Authors: **Valeria SORGATO^{1*}**, **Morris Krainz²**, **Tobias Brosch²** **Evelina Trutnevyte¹**

¹ Renewable Energy Systems, Institute for Environmental Sciences (ISE), Section of Earth and Environmental Sciences, University of Geneva, Switzerland

² Consumer Decision & Sustainable Behavior Lab, Department of Psychology, Faculty of Psychology and Educational Sciences (FPSE), University of Geneva, Switzerland

* Corresponding author (Uni Carl Vogt, Boulevard Carl Vogt 66, CH-1211 Geneva 4, Switzerland; +41 22 3791251; valeria.sorgato@unige.ch)

Abstract

Public acceptance is a critical factor for the successful implementation of climate mitigation measures. Yet, Integrated Assessment Models (IAMs) often exclude this social dimension and risk misjudging the real-world viability of the mitigation measures they are designed to model. This study examines how informed perceptions of feasibility-related uncertainties affect acceptance, support, and affect in the general population towards four IAM-modelled measures: bioenergy with carbon capture and storage (BECCS), green hydrogen, afforestation/reforestation, and sustainable diets. In a survey across six European countries (Germany, France, Italy, Spain, Poland, and the Netherlands; total N = 3,351), we found that providing uncertainty information lowered acceptance, support, and, to a lesser degree, affect, but all measures remained positively evaluated, and differences between measures and countries remained stable. Sustainable diets and BECCS were the least accepted, particularly in Poland and the Netherlands, where participants, on average, were opposed to sustainable diets. Higher perceived uncertainty, especially regarding social and technological feasibility, was negatively associated with acceptance and affect, an effect that strengthened after information, particularly for social uncertainty. Climate change beliefs emerged as the strongest predictor of acceptance among all predictive factors. Trust in scientists also contributed positively to acceptance of mitigation measures, while trust in government and sociodemographic variables showed marginal influence. Our findings underscore the importance of combining social factors with IAMs to better reflect real-world constraints and improve the design and communication of climate mitigation policies.

Keywords: acceptance, uncertainty, feasibility, carbon dioxide removal, climate change mitigation, informed citizens, integrated assessment models



HIGHLIGHTS

- All measures were positively evaluated, even after uncertainty communication
- Afforestation/reforestation ranked the most favorable, and sustainable diets the least
- Perceived social and technological uncertainties drove the opposition
- Information amplified the negative effect of perceived social uncertainty
- Climate change belief was the strongest driver of public support

1. Introduction

In democratic societies, public opinion generally serves as a key determinant of what kind of policy change can be considered possible and potentially successful ¹. In the urgent case of effectively mitigating climate change, widespread support can drive ambitious climate policy action, while a lack of it could present a major barrier to the low-carbon transition ^{1,2}. Limiting global temperature increase to 1.5 to 2°C by mid-century requires implementing a diverse portfolio of mitigation measures, ranging from engineered technological systems and extensive nature-based solutions to fundamental behavioral changes ³. However, as each of these measures carries its own distinct set of risks, benefits, limitations, and uncertainties, they can trigger varied responses from the public. It is therefore essential to distinguish levels of acceptance and support for various climate solutions to inform the design of more effective and socially acceptable policies ²⁻⁷.

One of the key tools used to guide mitigation policy decisions is Integrated Assessment Models (IAMs). While IAMs combine climate science, economics, energy systems, and land use considerations to analyze the human-technology-economy-climate interface, they often overlook the social acceptance dimension, potentially misjudging the real-world viability of the mitigation measures they aim to evaluate ⁸⁻¹¹. Prior research has investigated public attitudes towards frequently modelled mitigation measures in IAMs to a limited extent only, such as bioenergy with carbon capture and storage (BECCS), green hydrogen, afforestation and reforestation, and the shift toward sustainable diets ³. BECCS, for example, which involves using fast-growing vegetation for energy production while capturing and storing the released CO₂ underground, raises significant land-use concerns, as the cultivation of energy crops can compete with land for food production ^{3,4}. It also faces economic concerns due to the sophisticated and costly infrastructure required to capture, transport, and store CO₂ ^{3,4}. Green hydrogen prompts primary concerns about technical safety, particularly the perceived risk of gas leaks and explosions at storage facilities ^{2,5}. The renewable electricity-powered technology to produce hydrogen is also emerging and costly ¹². Even afforestation and reforestation, though generally perceived positively, can encounter social and environmental opposition related to land-use conflicts and improper implementation, such as using invasive plant species ³. Shifts toward sustainable diets, which involve shifting toward a more plant-based protein diet, often encounter socio-cultural resistance to changes in long-held culinary traditions ^{6,7}.

More so, accurately understanding and modelling potential deployment levels of these mitigation measures when considering public acceptance ideally requires the elicitation of informed preferences. Informed preferences allow for bridging the gap between the descriptive and factual reality of *what is* (i.e., how people currently think about a technology) and the normative ideal of *what should be* (i.e., how a person would think about a technology to best serve their values)^{13,14}. Most surveys on public acceptance do not elicit informed preferences and consequently may be susceptible to distortions by public misconceptions and knowledge gaps^{12,15,16}. This raises the question of whether the usually applied surveying practices are reliable foundations to guide policy and are suitable for informing IAMs^{17–19}. This is especially important for complex issues such as climate change mitigation measures, where knowledge gaps still exist².

Moreover, studies measuring informed preferences of specific mitigation measures have primarily focused on providing information about the risks and benefits^{19–21}. Yet, to elicit real preferences aligned with people's values, it is also important to inform about the uncertainties surrounding the potential outcomes and about the various dimensions that contribute to the feasibility of the mitigation measure (e.g., geophysical, technological, economic, social, institutional, or environmental feasibility)^{14,22}. First, people may overlook uncertainties about a measure's effectiveness due to insufficient knowledge about the measure itself, which, when eventually considered, can reduce public support^{15,23–26}. Second, the public's perception of uncertainties may be much higher than estimates from formal scientific assessments due to misconceptions²⁶. Third, public acceptance is highly sensitive to the degree of uncertainty across various feasibility dimensions that, in turn, are uniquely important to particular mitigation measures and thus may affect acceptance differently³. Therefore, we argue that a view formed in ignorance of uncertainties related to a measure's mitigation potential and its various feasibility dimensions is not a robust reflection of a person's values and is unlikely to be a stable predictor of their future behavior.

While analyzing how uncertainty perceived by informed citizens influences acceptance, a purely cognitive assessment provides only a partial picture, as emotions are also powerful drivers of climate policy acceptance^{23–27}. As Lan Gao et al.²³ demonstrate, perceived uncertainty generates negative emotions towards personal carbon trading policy, which, in turn, strongly inhibits public acceptance. Affective responses are particularly important under conditions of high uncertainty, where intuitive and emotional processes often guide decisions. For instance, Klaus et al.²⁸ found that participants used their "affect heuristic", a gut emotional feeling, to guide their acceptance of unknown technologies like BECCS²⁹. Conversely, some researchers argue that when outcomes evoke strong emotional responses, people tend to overlook the likelihood of such outcomes, focusing instead on the impact of potential results rather than their uncertainties^{30,31}. Therefore, a full understanding of public views on mitigation measures requires assessing not only cognitive acceptance but also the affective responses that guide judgments under uncertainty.

While a substantial body of literature has examined the impact of uncertainty information and perceived uncertainty on climate policy acceptance ^{22,23}, including the interplay with affect ²⁹, there is an unexplored research gap in the literature that compares how providing information about different feasibility-related uncertainties distinctly influences acceptance of and affect towards several mitigation measures. Additionally, there is only limited research providing cross-country informed evaluations that could be fit-for-purpose for global or regional modelling purposes ⁴. Moving beyond baseline attitudes and initial impressions, we therefore measured informed acceptance, support, and affect in a large-scale, cross-country analysis in Germany, France, Italy, Spain, Poland, and the Netherlands of four key mitigation measures used in IAMs: afforestation/reforestation, green hydrogen, BECCS, and sustainable diets. We aimed to answer the following research questions:

1. What are the initial and informed ratings of acceptance, support, and affect of citizens in Germany, France, Italy, Spain, Poland, and the Netherlands regarding BECCS, green hydrogen, afforestation and reforestation, and a shift towards sustainable diets?
2. How does perceived uncertainty across different feasibility dimensions (geophysical, technological, economic, and social) and mitigation potential influence public acceptance, support, and affect towards climate mitigation measures, and how does this change after receiving uncertainty information?
3. Which other individual factors (political trust, trust in climate scientists, climate change beliefs, socio-demographic characteristics) influence acceptance, support, and affect towards these measures?

2. Methodology

2.1 Procedure and structure of the survey

The survey was built in Qualtrics and distributed, via an external panel provider, in the six highest-emitting countries of the European Union (Germany, France, Italy, Spain, Poland, and the Netherlands). Together, these countries accounted for 72% of the EU's total direct greenhouse gas (GHG) emissions in 2023 ³². The survey was translated into six languages and reviewed by native speakers in each country to ensure clarity and accuracy. Institutional ethical approval was obtained for the study before the launch of the survey.

In order to compare initial and informed evaluations, we provided participants with information about uncertainties related to each measure's feasibility (*geophysical, technological, economic, and social*) and *mitigation potential* levels ^{3,27}. Our analysis then sought to explain the influence of perceived feasibility-related uncertainty on *acceptance, support, and affect* before and after the provision of information. For a complete picture, we

additionally assessed the relative importance of other critical drivers like *climate change beliefs*, *political trust*, *trust in climate scientists*, *subjective knowledge*, and socio-demographic factors. The full survey structure and English version of the questionnaire are available in Sections A.1 and A.2 of the Supplementary Material.

The survey consisted of three blocks. In the first block, we assessed participants' commitment and attention, and collected sociodemographic data, including *gender*, *age*, *education level*, and *income*. Participants who did not commit to paying attention, failed the attention check, or were younger than 18 years old were screened out. The survey continued with self-assessed scales on *climate change beliefs*, *political trust*, and *trust in climate scientists*, presented in randomized order (see Section 2.2 for details about measures). At the beginning of the second survey block, participants were randomly assigned to receive information about one of the mitigation measures: BECCS, afforestation/reforestation, green hydrogen, or sustainable diets ($N \approx 838$ per group). First, participants were asked to rate their *subjective knowledge* about the mitigation measure. They were then presented with a general and non-biased text describing the mitigation measure, followed by an attention check to screen out those participants who had not read the information carefully. After reading the introductory text, participants were asked to indicate their initial *acceptance*, *support*, and *affect* towards the mitigation measures. Then, participants were asked to rate their *perceived uncertainty* regarding the *mitigation potential* and the four feasibility dimensions (*geophysical*, *technological*, *economic*, and *social*) of the mitigation measure. To measure *objective knowledge*, participants answered a multiple-choice question about the uncertainties related to the mitigation measure's feasibility dimensions and potential. In the third block, participants were presented with detailed and non-biased information about these uncertainties. Following this, participants' *objective knowledge* was measured again, and they were asked to indicate their informed *acceptance*, *support*, and *affect* based on this additional information. At the very end, participants were asked to rate their *support* for policies that aimed to reach different *mitigation potential* levels for the assigned measure. For example, participants were asked how much they would support the implementation of BECCS if the goal was to remove different amounts of CO₂ eq per year: more than 5 gigatons, between 2.5 and 5 gigatons, between 1 and 2.5 gigatons, or only 1 gigaton.

2.2 Measures

Beliefs and trust

Climate change beliefs were measured using seven items adapted from Van Valkengoed et al.³³ and Krainz et al.³⁴, covering beliefs about climate change reality, human causes, negative consequences, spatial proximity, temporal distance, climate worry, and personal responsibility. All items showed strong internal consistency (Cronbach's $\alpha = 0.90$). Political trust was measured using six items adapted from Spampatti et al. (2023)³⁵, grouped into three subscales with two items each: value similarity (Cronbach's $\alpha = 0.86$), credibility (Cronbach's $\alpha = 0.88$), and competence (Cronbach's $\alpha = 0.84$). Together, these formed a highly reliable composite measure of political trust (Cronbach's $\alpha = 0.94$). Trust in climate scientists

was assessed using six items adapted from the credibility factors proposed by Gaziano and McGrath (1986) ³⁶. We selected the six items that aligned most closely with perceptions of trust in climate scientists and that showed the highest factor loadings. These items assessed whether climate scientists are biased, tell the whole story, are accurate, separate facts from opinions, can be trusted, and tend to be sensationalist. The measure, with six items of trust in climate scientists, showed internal consistency (Cronbach's $\alpha = 0.87$). All items used for climate change beliefs, political trust, and trust in climate scientists were rated on a 7-point Likert scale ranging from -3 (strongly disagree) to +3 (strongly agree).

Knowledge

Subjective knowledge was measured using a 5-point Likert scale from 1 (No knowledge) to 5 (Very good knowledge) using a single-item question adapted from Krainz et al. ³⁴ and Volken et al. ²¹. To assess objective knowledge ²¹, participants were asked to respond to five True/False quiz questions specifically constructed for each mitigation measure based on its feasibility dimensions and its associated uncertainties.

Acceptance/Support

We measured acceptance and support towards mitigation measures using two four-item subscales adapted from Kyselá and colleagues ³⁷: policy acceptance (Cronbach's $\alpha = 0.95$) and potential support (Cronbach's $\alpha = 0.91$), measured in a 7-point Likert scale from -3 (lower acceptance or support) to +3 (higher acceptance or support). As these two subscales were highly correlated ($r_{\text{initial}} = 0.84$; $r_{\text{informed}} = 0.88$), they were combined into a single scale with excellent internal consistency (Cronbach's $\alpha = 0.95$). For our results, we will refer to this combined measure as *acceptance/support*.

Support for mitigation potential levels

To measure support for the specific levels of policy implementation, participants rated their support for four distinct *mitigation potential* levels for their assigned measure. This was a self-constructed item where evaluations were rated on a 5-point Likert scale from -2 (strongly oppose) to +2 (strongly support). These potential levels were presented sequentially, in a carousel format, starting from a measure-specific maximum target – set at 0.5 GtCO_{2-eq}/yr below the highest best estimated potential for each mitigation measure – and decreasing in two nearly equal ranges to a common minimum (up to 1 GtCO_{2-eq}/yr). The specific ranges for the intermediate potential level were tailored to each mitigation measure's scientifically estimated potential from the Sixth Assessment Report of the IPCC ³. For instance, participants evaluating sustainable diets first rated their support for a potential of "3 GtCO_{2-eq} or more," followed by "between 2 and 3 GtCO_{2-eq}," then "between 1 and 2 GtCO_{2-eq}," and finally "up to only 1 GtCO_{2-eq}."

Affect and emotions

To assess affect, participants were asked to report how they felt about the mitigation measure using a single affect item adapted from Spampatti et al. ³⁸ rated on a -3 (very negative) to +3

(very positive) 7-point Likert scale. Additionally, we measured the discrete emotions of worry, anger, fear, hope, and pride ³⁴. Each emotion was assessed on a –3 (strongly disagree) to +3 (strongly agree) 7-point Likert scale.

Perceived uncertainty

Perceived uncertainty regarding the feasibility of the mitigation measures was assessed across five items, one for each of the feasibility dimensions (*geophysical, technological, economic, social*) and the overall *mitigation potential* (adapted from Bles et al.) ²². Each item was rated on a 7-point Likert scale ranging from –3 (very certain) to +3 (very uncertain). Combined, these five items showed excellent internal consistency (Cronbach's $\alpha = 0.91$).

2.3 Mitigation measures and their feasibility dimensions

The choice of mitigation measures and feasibility dimensions was made based on a review of the scientific literature, including the Sixth Assessment Report of the IPCC ³. The mitigation measures were selected to represent a diverse portfolio, ranging from technological and nature-based solutions to behavioral changes, each characterized by different levels of uncertainty. BECCS, the most uncertain among the selected measures, is one of the most common negative emission technologies used in IAMs, with a *mitigation potential* of up to 6 gigatons of CO_{2-eq} per year. Afforestation and reforestation, one of the least uncertain in the technological and economic point of view, represent nature-based negative emissions solutions, potentially reducing up to 5 gigatons of CO_{2-eq} per year. It is largely used by IAMs due to its large potential to reduce direct CO₂ emissions from the atmosphere. Green hydrogen, the second most uncertain, is an emerging energy carrier and technology that has lately been proposed as a key solution in low-emission scenarios for hard-to-electrify sectors, such as industry and transport, with an estimated *mitigation potential* of around 3 gigatons of CO_{2-eq} per year ^{39,40}. Finally, sustainable diets, the least uncertain from the geophysical and technological point of view, offer the highest demand-side *mitigation potential* at 3.5 gigatons of CO_{2-eq} per year ³.

To assess the real-world implementation challenges of these climate mitigation measures, our study drew on the IPCC's feasibility framework, which evaluates mitigation measures across six dimensions ^{3,27}. To avoid overwhelming the participants, we selected four of the six dimensions for our analysis: *geophysical, technological, economic, and social* feasibility. These were chosen as they represent the most prominent sources of uncertainty for the measures in our study. For instance, *geophysical* feasibility, defined by the availability of natural resources, is a primary concern for land-intensive measures ^{3,27}. Afforestation/reforestation and BECCS face uncertainty about securing the vast land requirements for their *mitigation potential* (320-970 million hectares for BECCS alone) without conflicts with food production and biodiversity, especially amid climate unpredictability and resource scarcity ⁴¹⁻⁴³. *Technological* feasibility, or the ability to rapidly scale up infrastructure, is a key uncertainty for green hydrogen and BECCS ^{3,27}. Both emerging technologies require a multi-thousand-fold increase in current global capacity to meet climate targets, a goal clouded by uncertainty over

investment, supply chains, and innovation pace ^{43,44}. *Economic* feasibility is another critical uncertainty, particularly for capital-intensive solutions like green hydrogen and BECCS, where unpredictable future costs can deter private investment and public support ^{12,39,42,43}. Finally, *social* feasibility, relating to public willingness to adopt new behaviors and accept new options, represents a main barrier for sustainable diets ^{3,7,27}. Sufficient plant-based proteins are already produced globally to feed today's world population; thus, the fundamental uncertainty is not one of supply, but whether diverse societies and cultures can make such a consumption shift ⁴⁵.

2.4 Informational material

At the beginning of the second block of the survey, participants first received a general explanation of the climate change mitigation measures (either *BECCS*, *afforestation/reforestation*, *green hydrogen*, and *sustainable diets*). This text also included the IPCC's best estimate of the measures' *mitigation potential* ³. To support understanding, the information was accompanied by a bar chart comparing current global annual CO₂-eq emissions with projected emissions assuming implementation of the assigned measure, thereby visualizing the potential emissions reduction. The primary objective of this introductory text was to provide a common factual baseline among participants. Section A.2 in the Supplementary Material provides the English version of the survey.

The second point at which participants received information occurred at the beginning of the third survey block. Here, they were presented with detailed information about the uncertainties associated with the four feasibility dimensions of the measure: *geophysical*, *technological*, *economic*, and *social*. The text first clarified that the best-estimate *mitigation potential* of the measure was uncertain and provided a quantitative range. It then explained that this uncertainty stemmed from the varying levels of uncertainty across different feasibility dimensions. Each dimension was subsequently described concisely in one to two sentences, summarizing the main uncertainties. This explanation was accompanied by the same bar chart used earlier for the background information, now illustrating the uncertainty range of the *mitigation potential*. This section aimed to inform participants about the uncertainties associated with the mitigation measure and to assess their informed views and perceptions after reading the information.

The final materials were reviewed and approved by 20 experts in the field. To ensure consistency and minimize potential framing effects, both the background and detailed information on uncertainty followed a consistent structure and used similar wording across all mitigation measures.

2.5 Sample size and description

The survey was distributed during March and April of 2025. The required sample size was determined a priori using G*Power ⁴⁶ for a repeated measures ANOVA. The analysis was designed to detect a small interaction effect ($f= 0.1$) between the within-subject factor *Time*

(2 levels: pre, post) and the between-subject factor (4 levels: the mitigation measures). We specified a statistical power of $1 - \beta = 0.95$, an alpha level of $\alpha = 0.01$, and assumed a correlation of $r = 0.5$ among the repeated measures. This analysis recommended a total sample size of 576 participants. Given that we aimed to compare *acceptance*, *support*, and *affect* across countries and mitigation measures, we targeted a larger sample size of 3500 participants to ensure sufficient statistical power for robust subgroup analyses. We ensured a representative sample of each country's adult population using crossed quotas for *age* and *gender*, and a separate quota for *education* level. In total, 3812 participants completed the survey. To ensure data quality, we excluded participants who straight-lined more than 80% of questions ($n=91$), were identified as duplicates ($n=200$), and completed the survey in less than six minutes ($n=193$, mean = 21.3, median = 14.8). The final analysis sample comprised $N=3351$ participants. The final sample size varied across mitigation measures. For BECCS, it was $N=794$; for afforestation/reforestation, $N=863$, for green hydrogen, $N=851$, and sustainable diets, $N=843$. Country size sample also varied: France $N= 571$, Germany $N= 558$, Italy $N=573$, the Netherlands $N=521$, Poland $N= 562$, and Spain $N=566$.

In terms of *gender* distribution, all country samples had approximately equal percentages of female and male participants. The average *age* across countries was broadly representative, ranging from 45 to 49 years, with Poland having the youngest and Germany the oldest sample. *Education* levels were only nationally representative for Germany, due to a low response rate among participants with only primary education in the other countries. The Netherlands and Poland, thus, had the lowest proportions of participants with only primary education (2% and 4%, respectively), making the Dutch sample the most highly educated overall. In terms of income, Italy had the highest proportion of participants in the lowest income category (39%), while France had the largest share in the high income (12%). Middle-income earners constituted the largest proportion of participants in all countries except Germany, where low-income earners (37%) represented a larger share. The overall higher concentration of participants in the medium or medium-high income groups reflects a representative sample in these countries (See section A.3 of the Supplementary Material).

Concerning the *subjective knowledge*, participants reported on average little knowledge of the mitigation measures, with levels below the mid-point (< 3). French ($M= 2.18$, $SD= 1.05$) participants reported the lowest *subjective knowledge*, while Polish participants had the highest levels ($M=2.47$, $SD=1.06$). Whereas these country-level differences were not statistically significant, the *subjective knowledge* across mitigation measures differed significantly ($p < .001$), showcasing the different degrees of familiarity. Here, afforestation/reforestation ($M = 2.81$, $SD = 1.00$) and sustainable diets ($M = 2.65$, $SD = 1.00$) reported the highest levels, while BECCS ($M = 1.87$, $SD = 0.90$) and green hydrogen ($M = 1.98$, $SD = 0.99$) were perceived as the least familiar.

When examining prior beliefs and trust, participants across all countries reported low levels of *political trust* (with means below the Likert scale midpoint of 0). Dutch and Italian

participants were among the least trusting in government ($M = -0.75$; $M = -0.71$, respectively). *Trust in climate scientists* and *climate change beliefs* were consistently above the midpoint (>0), although Polish participants had a relatively lower *trust in climate scientists*, with reported levels closest to the midpoint ($M = 0.06$). Spanish participants reported the highest ratings in *climate change beliefs* ($M = 1.71$), whereas the Dutch and Polish samples rated the lowest ($M = 1.12$) (see Section A.3 in Supplementary Material).

2.6 Statistical Analysis

The analysis was conducted in four stages to evaluate informed public perceptions of climate mitigation measures and the main drivers for *acceptance/support* and *affect*. First, we used a series of repeated measures ANOVAs to assess changes in *objective knowledge*, *acceptance/support*, and *affect*, examining differences over time and across the various mitigation measures and countries. Second, we investigated the role of *perceived uncertainty*, using ANOVAs to assess changes from pre- to post-information and employing multilevel models to analyze its influence on *acceptance/support* and *affect*. This involved decomposing uncertainty into stable between-person traits and dynamic within-person states to understand its predictive power more deeply^{47–49}. Third, we interacted the undecomposed perceived uncertainty with time to observe how the delivery of information changed the influence of *perceived uncertainty* on *acceptance/support* and *affect*. Finally, we conducted multilevel models that simultaneously included *perceived uncertainty*, *climate change beliefs*, *trust in climate scientists*, *political trust*, and socio-demographic factors to isolate the most influential individual-level drivers of public *acceptance/support* and *affect*, controlling for all other variables to determine each predictor's unique contribution. A detailed explanation of the Statistical Analysis can be found in Supplementary Material A.4.

3. Results

3.1 Initial and informed acceptance/support and affect

To ensure that post-intervention evaluations could be considered informed, we measured participants' *objective knowledge* both before and after providing information. Initially, knowledge was low, with only 22% of participants answering more than three out of five questions correctly. The delivery of information proved highly effective, producing a large and significant overall increase in knowledge ($M_{diff} = 1.03$, $p < .001$, Cohen's $d = 0.78$). After receiving information, the proportion of participants scoring correctly in three or more questions rose to 57%. While knowledge increased for all measures, the magnitude of this gain varied. The gain was largest for BECCS ($M_{diff} = 1.28$, $SD = 1.35$) and smallest for sustainable diets ($M_{diff} = 0.57$, $p < .001$), which also had the lowest final knowledge score ($M = 3.19$, $SD = 1.23$). Given the significant increase in participants' knowledge after receiving information, their post-information *acceptance/support* and *affect* can be considered informed responses and contrasted with their initial evaluations (see Supplementary Material A.5).

Initial *acceptance/support* for all mitigation measures was, on average, above the midpoint (> 0) of the Likert scale (–3 to 3) as shown in Figure 1, yet it varied significantly across mitigation measures and countries. A clear order was present: afforestation/reforestation was the most favored measure ($M = 1.60$, $SD = 1.09$) followed by green hydrogen ($M = 1.20$, $SD = 1.11$), BECCS ($M = 0.58$, $SD = 1.36$), and finally sustainable diets ($M = 0.16$, $SD = 1.63$), which consistently received the lowest ratings (*all* p 's < .001). This ranking was mirrored in *affect* (see Supplementary Material A.6). While all measures were, on average, viewed positively, significant country-level variations were evident. Notably, the Dutch and Polish consistently reported lower *acceptance/support* and *affect* for most measures compared to other countries. For instance, initial *acceptance/support* for sustainable diets was negative in both countries ($M = -0.14$, $SD = 1.39$; $M = -0.39$, $SD = 1.67$, respectively), and significantly lower ($M = 0.37$, $SD = 1.19$; $M = 0.19$, $SD = 1.41$, respectively) for BECCS. An exception was afforestation/reforestation, for which Polish participants reported significantly higher initial *acceptance/support* ($M = 1.86$, $SD = 1.04$, $p < .001$) and *affect* ($M = 2.06$, $SD = 1.07$, $p < .01$) compared to the Netherlands. Conversely, Spanish participants often reported among the highest *acceptance/support* and positive *affect* levels, particularly for green hydrogen ($M_{\text{acc/supp}} = 1.56$, $SD_{\text{acc/supp}} = 1.08$; $M_{\text{aff}} = 1.51$, $SD_{\text{aff}} = 1.15$) and BECCS ($M_{\text{acc/supp}} = 1.12$, $SD_{\text{acc/supp}} = 1.30$; $M_{\text{aff}} = 1.09$, $SD_{\text{aff}} = 1.27$).



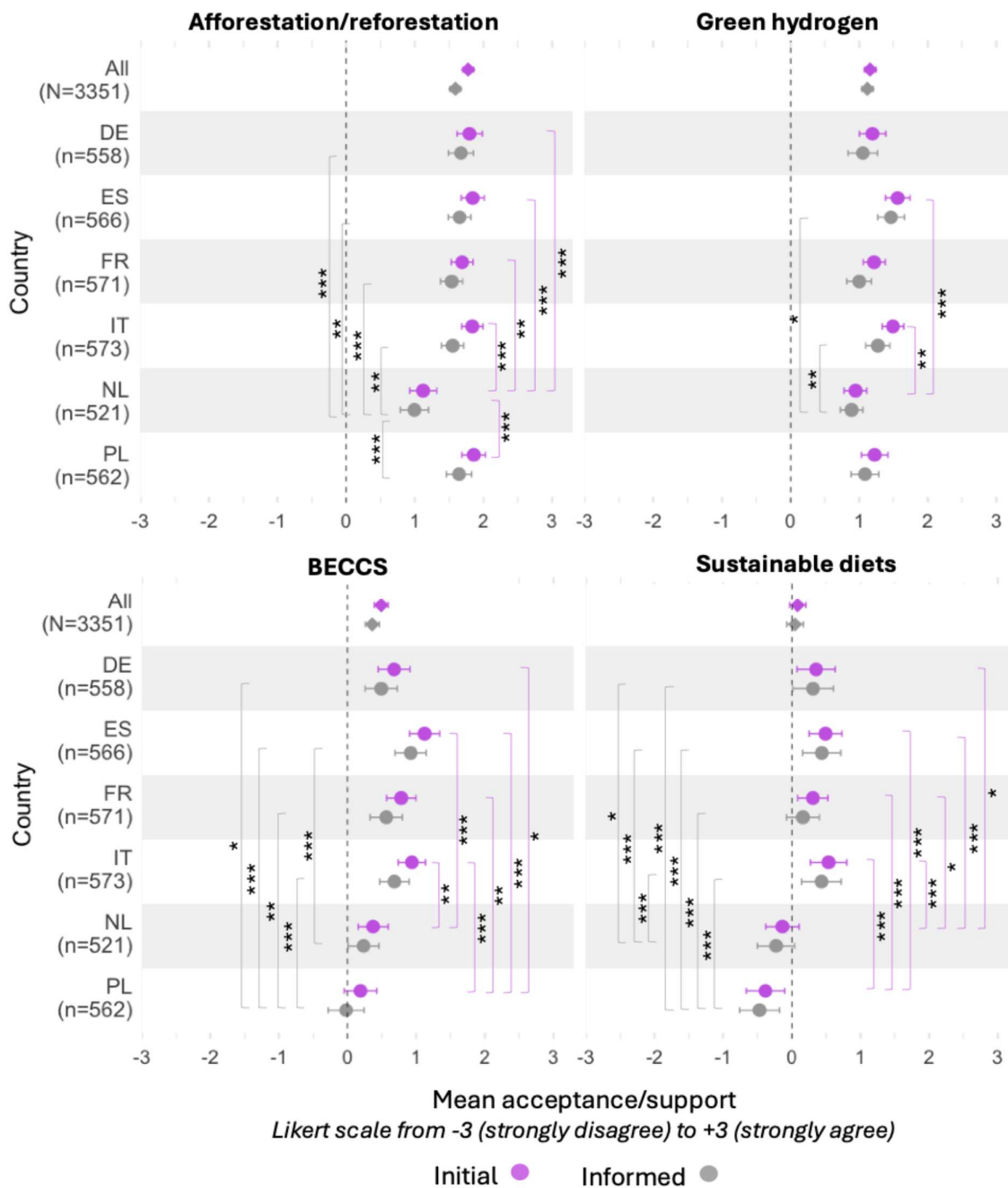


Figure 1. Initial and informed mean acceptance/support for each mitigation measure across countries. Points represent means with standard errors. Statistical differences between countries' initial (purple) and informed (gray) values are indicated by connecting lines and asterisks ($F: 3.35, p < .001$). Overall means between mitigation measures were all statistically significant ($F: 226, p < .001$). Significant differences were assessed using repeated measures ANOVA followed by Bonferroni-adjusted post hoc comparisons (see Supplementary Material A.4 for more information on the statistical analysis). Significance levels: * $p < .05$, ** $p < .01$, *** $p < .001$

After receiving information on feasibility-related uncertainties, participants showed a statistically significant overall moderate decline in *acceptance/support* ($\beta = 0.15$, $F = 198.6$, Cohen's $d = -0.24$, $p < .01$). The magnitude of this decline, however, differed by mitigation measure. *Acceptance/support* for sustainable diets, which started from the lowest baseline, experienced the smallest drop ($\beta = -0.09$, $t = 4.02$, Cohen's $d = -0.09$, $p < .001$), a significantly less pronounced change than that for BECCS ($\beta = -0.20$, $t = 8.98$, Cohen's $d = -0.31$, $p < .001$) ($p < .001$) and afforestation/reforestation ($\beta = -0.18$, $t = 8.46$, Cohen's $d = -0.28$, $p < .001$) ($p < .01$). *Affect* followed a similar, though weaker, trend ($\beta = -0.099$, $F = 52.5$, Cohen's $d = -0.12$), with significant declines observed only for BECCS ($\beta = -0.13$, $t = 4.6$, Cohen's $d = -0.16$) and afforestation/reforestation ($\beta = -0.19$, $t = 6.95$, Cohen's $d = -0.24$, both $p < .001$). The *affect* for sustainable diets and green hydrogen was least impacted by the information (both: $\beta = -0.04$, $t = 1.4$, Cohen's $d = -0.05$, $p = 0.13$ and 0.15 , respectively).

Despite these declines after information, the relative ranking of the four mitigation measures remained unchanged post-information (see Figure 1 and Supplementary Material A.6). Afforestation/reforestation retained its top position ($M_{acc/supp} = 1.51$, $SD = 1.09$; $M_{aff} = 1.59$, $SD = 1.17$), and sustainable diets remained the least favored ($M_{acc/supp} = 0.12$, $SD = 1.70$; $M_{aff} = 0.05$, $SD = 1.82$). The pre-existing country-level patterns also persisted. The Netherlands and Poland continued to report the lowest values, with average ratings for sustainable diets falling below the midpoint for both *acceptance/support* ($M = -0.23$, $SD = 1.54$; $M = -0.47$, $SD = 1.75$, respectively) and *affect* ($M = -0.29$, $SD = 1.70$; $M = -0.04$, $SD = 1.55$, respectively). Post-information, *acceptance/support* for BECCS also dropped below the midpoint in Poland ($M_{acc/supp} = -0.02$, $SD = 1.54$; $M_{aff} = -0.04$, $SD = 1.55$). Spain, in contrast, continued to show particularly high *acceptance/support* and *affect* for green hydrogen ($M_{acc/supp} = 1.46$, $SD = 1.16$; $M_{aff} = 1.51$, $SD = 1.15$) and BECCS ($M_{acc/supp} = 0.92$, $SD = 1.33$; $M_{aff} = 0.89$, $SD = 1.39$). Notably, post-information *affect* for the highly rated afforestation/reforestation remained uniformly positive across all countries, with no significant differences (see Supplementary Material A.6).

3.2 Informed support for different levels of mitigation potential

Consistent with our previous findings, the same order of preferences emerged when we asked participants to rate their *support* for policies aiming to achieve different levels of *mitigation potential* for their assigned measure. Across all potential levels, afforestation/reforestation received the highest *support*, followed by green hydrogen, BECCS, and finally sustainable diets (Figure 2). For all measures, there was a general trend of increasing *support* for higher *mitigation potentials*. For instance, the highest potential level for green hydrogen (>2.5 Gt CO_{2-eq}) received significantly more *support* ($M = 0.63$) than its lowest level (<1 Gt CO_{2-eq} , $M = 0.38$). This pattern held for the maximum potential of each measure, with *support* being highest for afforestation/reforestation ($M = 0.76$) and lowest for sustainable diets ($M = 0.18$).

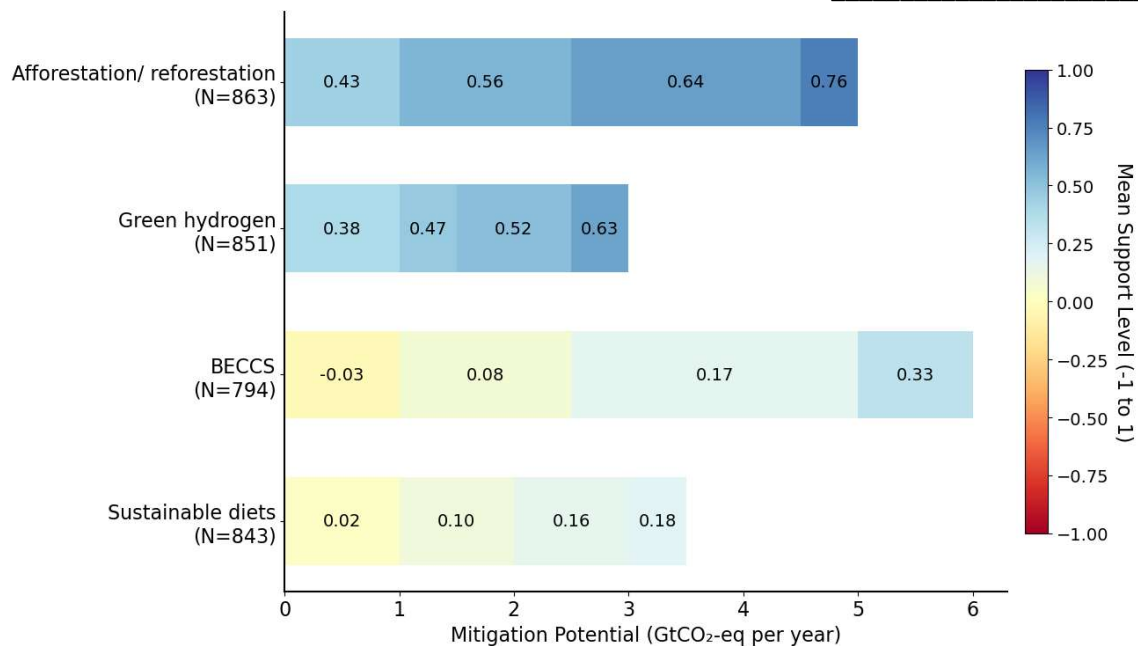


Figure 2. Mean support for different levels of mitigation potential. Numbers within the bars indicate the mean level of public support for each mitigation measure at a given mitigation potential level. The color gradient represents supportive or opposing levels: blue shades indicate positive support, red shades indicate opposition, and darker colors reflect stronger opinions. Support was measured on a Likert scale from -2 (strongly oppose) to $+2$ (strongly support). To better visualize the difference in means between mitigation potential levels, we used a scale from -1 to $+1$.

To explore these patterns more thoroughly, we divided participants into *supporters* (those with overall acceptance/support towards the mitigation measure above 0, $N=2461$) and *opposers/undecided* (with acceptance/support below or equal to 0, $N=886$) (see Supplementary Material A.7). This revealed two distinct patterns. Among *supporters*, there was a clear and consistent trend for all four measures: support systematically increased for higher mitigation potential levels. In contrast, *opposers/undecided* showed consistently negative support across all potential mitigation levels for all measures, indicating a general opposition to any scale of implementation. However, the intensity of this opposition varied. For BECCS and sustainable diets, opposition was strong and relatively uniform across all potential mitigation levels, with mean support values consistently around -0.55 . For afforestation/reforestation and green hydrogen, however, opposition was lower at higher potential mitigation levels, with average support ranging from approximately -0.11 to -0.34 . These two patterns behind *opposers/undecided* and *supporters*, with the latter being much more common, produced the overall result from Figure 2.

3.3 Effects of perceived uncertainty on acceptance/support and affect

Having established that acceptance/support and affect varied significantly across the four mitigation measures, we next sought to understand the underlying drivers of these

differences. We hypothesized that these evaluations were influenced by how much uncertainty participants perceived about each measure's feasibility and *mitigation potential*. To analyze the effect of *perceived uncertainties* on the *acceptance/support* and *affect* towards the mitigation measures, we began our analysis by examining the initial *perceived uncertainty* of the four mitigation measures. The descriptive statistics revealed a clear pattern: initial levels of public *acceptance/support* and *affect* were inversely related to *perceived uncertainty*. For instance, afforestation/reforestation, the most highly *accepted/supported* measure and with most positive *affect*, was also characterized by the lowest levels of *perceived uncertainty* across all dimensions: *mitigation potential* ($M=-0.43$, $SD=1.44$), *social* ($M=-0.73$, $SD=1.35$), *economic* ($M=-0.64$, $SD=1.33$), *technological* ($M=-0.51$, $SD=1.36$) and *geophysical* ($M=-0.45$, $SD=1.35$). Conversely, sustainable diets, the least *accepted/supported* measure and with the most negative *affect*, exhibited the highest levels of initial overall *perceived uncertainties* for all dimensions: *mitigation potential* ($M=0.32$, $SD=1.53$), *social* ($M=0.36$, $SD=1.54$), *economic* ($M=0.04$, $SD=1.49$), *technological* ($M=0.21$, $SD=1.49$), and *geophysical* ($M=0.17$, $SD=1.51$). (see Supplementary Material A.8). A closer look at the emotional responses revealed that the most favored mitigation measures not only elicited stronger feelings of hope than the least favored measures but were also the only ones to generate positive feelings of pride (see Supplementary Material A.9).

This inverse relationship persisted even after the delivery of information, which significantly increased perceived uncertainty across all dimensions and for all measures ($\beta_{\text{potential}} = -0.32$, $\beta_{\text{eco}} = -0.32$, $\beta_{\text{geo}} = -0.36$, $\beta_{\text{tech}} = -0.23$, $\beta_{\text{soc}} = -0.39$, for all $p < .001$). The information prompted the largest increase in composite uncertainty for BECCS ($M_{\text{diff}} = 0.3$, $SD=0.69$, Cohen's $d = 0.42$), causing it to become the most uncertain measure post-information (total uncertainty: $M=0.46$, $SD=1.17$). However, this was not significantly different from sustainable diets, which were least affected by the information ($M_{\text{diff}} = 0.07$, $SD=0.58$, Cohen's $d = 0.12$) and had already high uncertainty. Despite these shifts, afforestation/reforestation remained the least uncertain measure after information was delivered (total uncertainty: $M=-0.25$, $SD=1.15$) (see Supplementary Material A.8). To understand the nature of this relationship more deeply, we decomposed uncertainty into two components: stable between-person differences and dynamic within-person changes (Supplementary Material A.10). The resulting multilevel model explained a substantial amount of variance. The fixed effects alone accounted for 41-42% of the variance in *acceptance/support* and *affect* (Figure 3). The results confirmed that participants who were, generally, more uncertain also showed lower levels of *acceptance/support* and *affect* for all mitigation measures. This between-person effect was strongest for *perceived technological* ($\beta_{\text{acc/supp}} = -0.37$; $\beta_{\text{aff}} = -0.36$) and *social uncertainty* ($\beta_{\text{acc/supp}} = -0.29$; $\beta_{\text{aff}} = -0.32$), compared to the other uncertainties (all, $p < .001$).

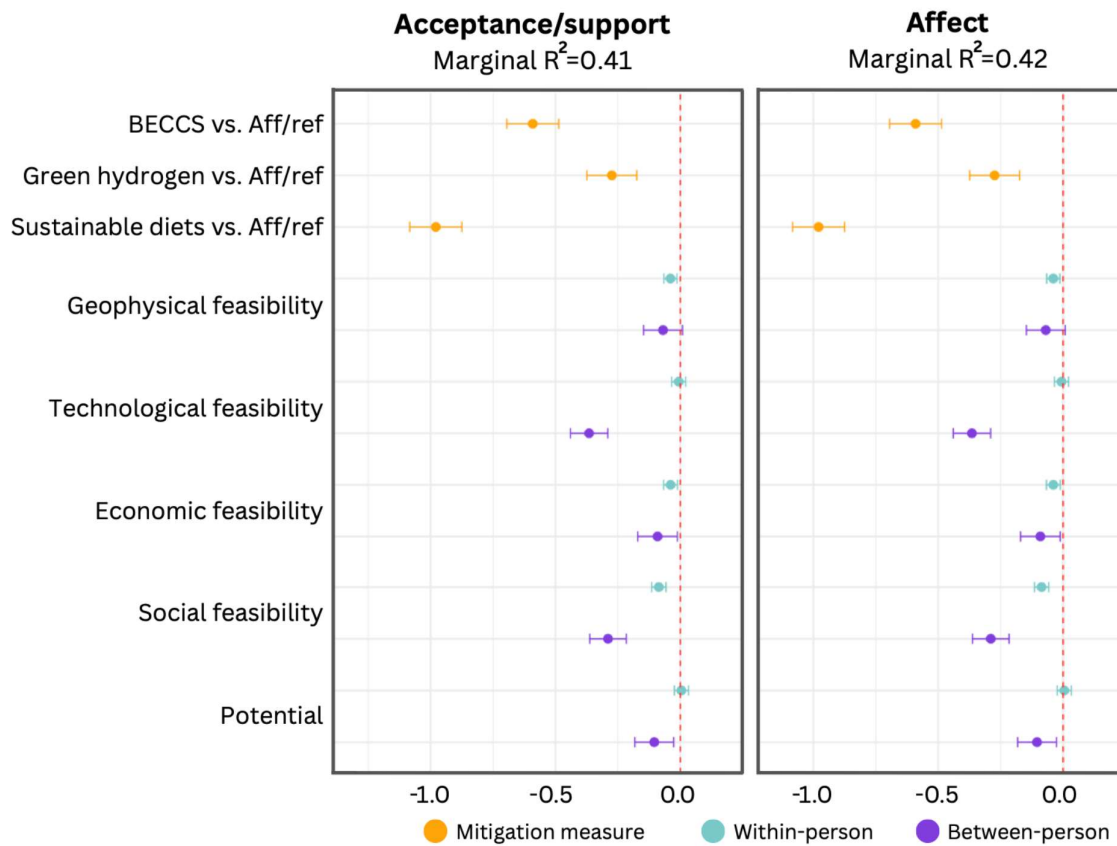


Figure 3. Between- and within-person effect of perceived uncertainty on acceptance/support and affect. This figure shows the unstandardized regression coefficients (β) and 95% confidence intervals from two multilevel models, one predicting acceptance/support and the other affect. Each model includes between-person effects (purple) and within-person effects (blue), and controls for mitigation measures (orange; relative to afforestation/reforestation as the reference category). Effects are considered statistically significant at the 95% confidence level if their confidence intervals do not cross zero (red dashed line). Negative coefficients indicate lower acceptance/support or affect associated with higher perceived uncertainty. The marginal R^2 value indicates the proportion of variance explained by the predictor variables only. A table representing this graph can be found in Supplementary Material A.10.

These effects remained robust across all mitigation measures in separate multilevel models, where both *perceived technological* and *social uncertainties* consistently emerged as strong and significant negative predictors of *acceptance/support* and *affect* (see Supplementary Material A.10). Other *perceived uncertainties* were highly specific to the nature of the measure. Only for the more land-intensive measures of BECCS and afforestation/reforestation, *perceived geophysical uncertainty* was a significant negative predictor on both *acceptance/support* ($\beta = -0.24, p < .001$; $\beta = -0.11, p < .05$, respectively) and *affect* ($\beta = -0.33, p < .00$; $\beta = -0.13, p < .05$, respectively). On the other hand, only sustainable diets showed a significant negative association between *perceived economic uncertainty* and *acceptance/support* ($\beta = -0.21, p < .05$), as well as between *perceived mitigation potential uncertainty* and both *acceptance/support* and *affect* ($\beta = -0.21$ and -0.19 , respectively, both p 's

< .05). Interestingly, *perceived economic uncertainty* had a different impact on technology-based measures, predicting more negative *affect* for BECCS ($\beta = -0.21$) and green hydrogen ($\beta = -0.15$, both p 's < .05).

Turning to the dynamic component of uncertainty, we examined the within-person effects, which reflect how an increase or decrease in an individual's *perceived uncertainty* relates to their average *acceptance/support* and *affect* towards the mitigation measure (see Figure 3). These effects, while more modest than the stable between-person differences, revealed that momentary increase in individuals' *perceived uncertainty*, relative to their average, about *social* ($\beta_{acc/supp} = -0.09$, $p < .001$; $\beta_{aff} = -0.04$, $p < .05$), *economic* ($\beta_{acc/supp} = -0.04$, $p < .01$; $\beta_{aff} = -0.08$, $p < .001$), and *geophysical* ($\beta = -0.04$, $p < .001$, both) feasibility were all associated with lower *acceptance/support* and *affect*. Fluctuation in *affect* was, in addition, slightly influenced by *perceived potential uncertainty* ($\beta_{acc/supp} = -0.04$, $p < 0.05$). A measure-specific analysis of these within-person effects revealed that temporary increase in *perceived social* and *economic uncertainties* was commonly associated with a decrease in *acceptance/support* across all measures (Supplementary Material A.10). Temporary increase in *perceived social* uncertainty predicted lower *acceptance/support* for BECCS, green hydrogen, and afforestation/reforestation (β range from -0.04 to -0.05, all p 's < .001), though it only predicted lower *affect* for afforestation/reforestation ($\beta = -0.04$, $p < .01$). *Perceived economic uncertainty*, in contrast, was a significant predictor of both lower *acceptance/support* and *affect*, but only for the two non-technological measures: afforestation/reforestation ($\beta_{acc/supp} = -0.03$; $\beta_{aff} = -0.04$, both $p < .05$) and sustainable diets ($\beta_{acc/supp} = -0.03$, $p < .01$; $\beta_{aff} = -0.07$, $p < .001$).

3.4 Impact of information and perceived uncertainty

To understand how information shaped the influence of *perceived uncertainty* on *acceptance/support* and *affect*, we tested whether information moderated the overall negative relationship by including an interaction between time (pre and post information) and raw *perceived uncertainty* scores in a multivariable linear mixed-effects model, and controlled by mitigation measures (Supplementary Material A.4). This model explained 23% of the variance in the fixed effects for *acceptance/support* ($R^2_{\text{marginal}} = 0.23$, $R^2_{\text{conditional}} = 0.88$) and 27% for *affect* ($R^2_{\text{marginal}} = 0.27$, $R^2_{\text{conditional}} = 0.84$) (see Figure 4 and Supplementary Material A.11). Results showed a statistically significant, yet small, amplification of *perceived uncertainty's* effect on *acceptance/support*, driven mainly by *perceived social uncertainty* ($\beta_{\text{diff}} = -0.04$, $p = .009$) (Figure 4). A measure-specific analysis revealed that the negative impact of *perceived social uncertainty* was mostly strengthened for BECCS ($\beta_{\text{diff}} = -0.08$, $p = .014$) and sustainable diets ($\beta_{\text{diff}} = -0.07$, $p = 0.019$). For *affect*, the information showed different effects on the predictive power of *perceived uncertainty*. While the negative effect of *perceived potential uncertainty* was significantly amplified overall ($\beta_{\text{diff}} = -0.05$, $p = .024$), the information intervention paradoxically weakened the negative influence of *perceived technological uncertainty* ($\beta_{\text{diff}} = 0.05$, $p = .009$) (Supplementary Material A.11). At the mitigation-measure level, this weakening of *perceived technological uncertainty's* effect was driven specifically by sustainable diets (β_{diff}

= 0.11, $p = .017$), whereas the amplification of *perceived potential uncertainty* was attributable to green hydrogen ($\beta_{diff} = -0.09$, $p = .031$).

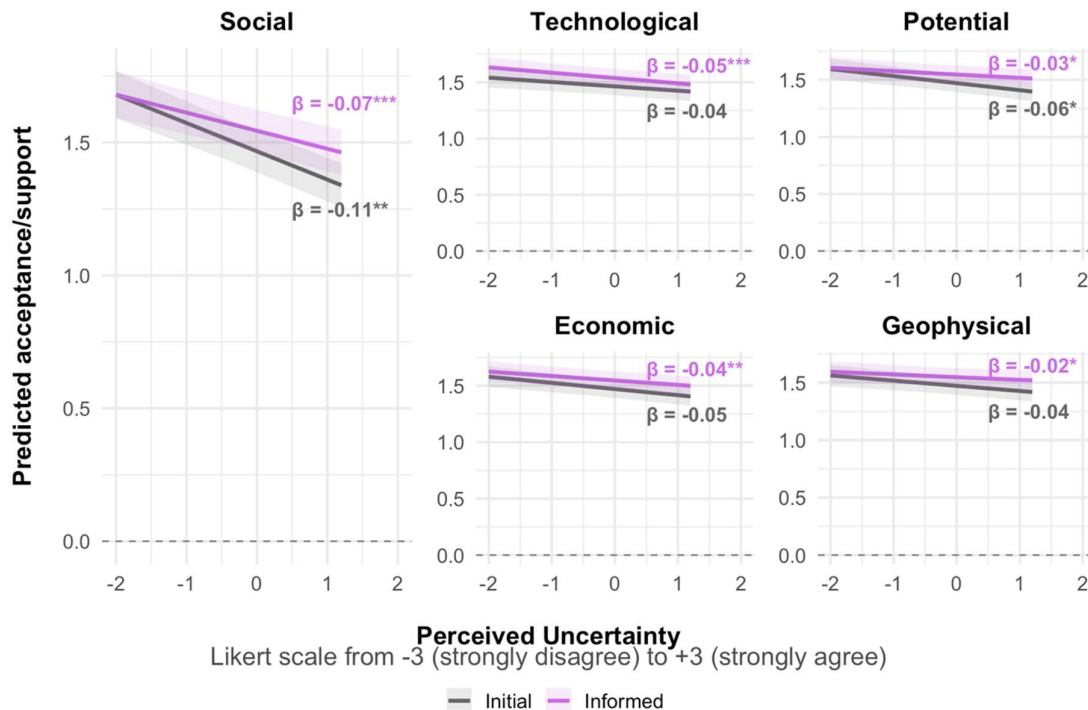


Figure 4. Change in the influence of perceived uncertainty on acceptance/support. The figure displays the predicted relationship between perceived geophysical, technological, economic, potential, and social uncertainties and acceptance/support, both before (initial, purple) and after (informed, gray) information. Slopes are derived from a single multivariable multilevel model that includes the interaction between time and each feasibility uncertainty, while controlling for mitigation measures. Shaded bands represent 95% confidence intervals. The annotated slope value (β) at the end of each line represents the unique predictive power of that uncertainty dimension at that time point. An asterisk (*) next to the "Informed" slope indicates that the change in the slope from Initial to Informed was statistically significant. Significance levels: * $p < .05$, ** $p < .01$, *** $p < .001$.

3.5 Effect of beliefs, trust, knowledge, and socio-demographic factors

While the preceding analyses established *perceived uncertainty* as a key driver of *acceptance/support* and *affect*, we next sought to understand the role of other influential individual and independent factors. Hence, we examined the predictive power of beliefs and trust (*climate change belief*, *trust in scientists*, *political trust*), key socio-demographic factors (*age*, *gender*, *income*, *education*), and participants' *subjective knowledge*, while accounting for between and within values of *perceived uncertainty* and controlling for the mitigation measure (Supplementary Material A.4.). This full model provided an excellent fit to the data, with its fixed effects explaining 53% of the variance in *acceptance/support* ($R^2_{\text{marginal}} = 0.53$, $R^2_{\text{conditional}} = 0.90$) and 51% of the variance in *affect* ($R^2_{\text{marginal}} = 0.51$, $R^2_{\text{conditional}} = 0.87$) (see Figure 5 and Supplementary Material A.12).

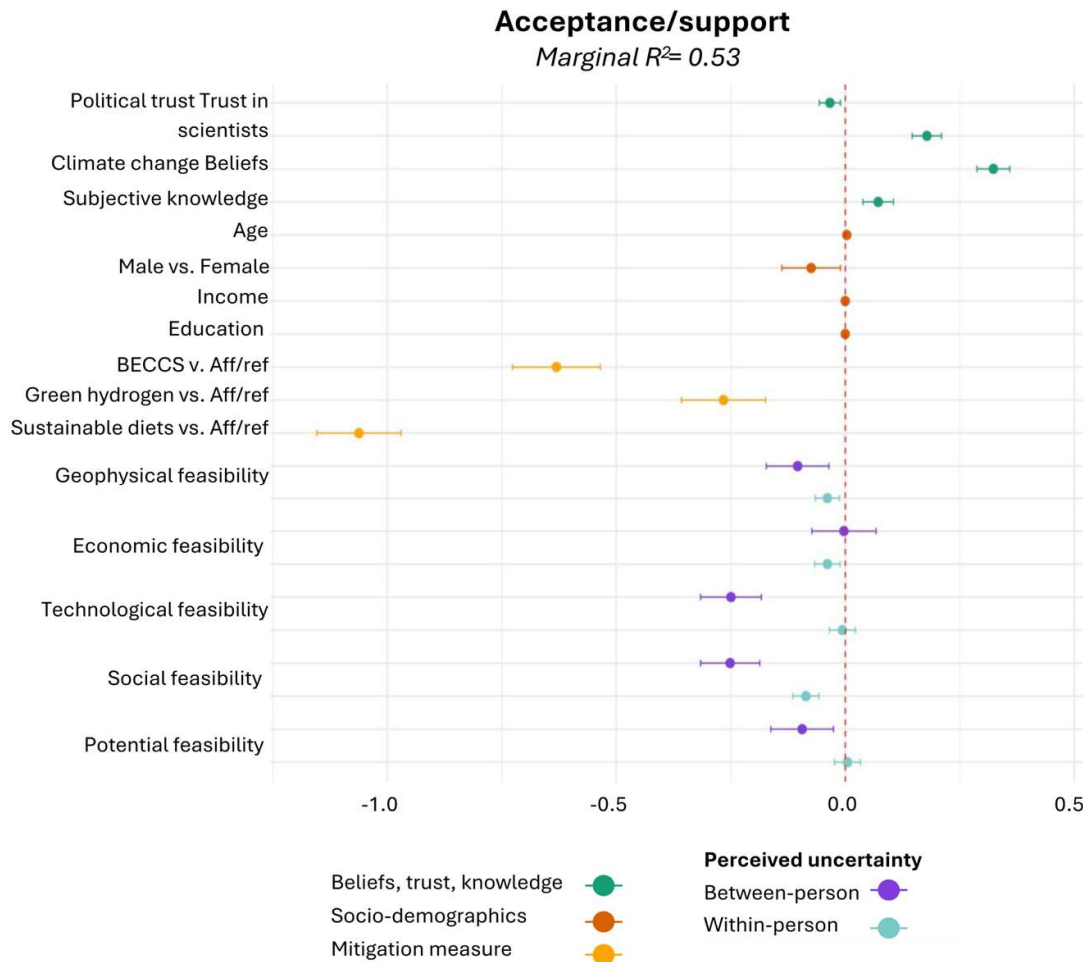


Figure 5. Fixed-effect estimates from a multilevel mixed model predicting acceptance/support as a function of beliefs, trust, knowledge, sociodemographic characteristics, and perceived uncertainties. Variables include beliefs, trust, and subjective knowledge (green); socio-demographic characteristics (red; gender is relative to female); mitigation measure type (orange; relative to afforestation/reforestation); between-person (purple) and within-person (blue) perceived uncertainty effects. Effects are considered statistically significant at the 95% confidence level if their confidence intervals do not cross zero (red dashed line). Positive values indicate higher acceptance/support associated with stronger beliefs, trust, or higher subjective knowledge; negative values indicate lower acceptance/support with higher perceived uncertainty or when compared to the reference category. The marginal R^2 value indicates the proportion of variance explained by the predictor variables only. A table representing this graph can be found in Supplementary Material A.12.

Within these models, *climate change belief* emerged as the strongest positive predictor of both *acceptance/support* ($\beta = 0.32, p < .001$) and *affect* ($\beta = 0.29, p < .001$). *Trust in climate scientists* was also a significant positive predictor, though its influence was more moderate ($\beta = 0.18$ for both outcomes, $p < .001$). In contrast, *political trust* had a practically negligible negative effect for both *acceptance/support* ($\beta = -0.03, p < .01$) and *affect* ($\beta = -0.04, p < .001$). Alongside these core beliefs, *perceived uncertainty* remained as a strong predictive factor. Specifically, stable between-person differences in *perceived technological* ($\beta_{acc/supp \text{ and } aff} = -0.25$) and *social uncertainty* ($\beta_{acc/supp} = -0.25; \beta_{aff} = -0.29$) proved to be nearly as influential as

climate change beliefs, though, of course, negatively associated with *acceptance/support* and *affect* (all $p < .001$).

Finally, several socio-demographic and knowledge variables emerged as significant, albeit modest, predictors for *acceptance/support* and *affect*. *Age* was positively associated, indicating that older participants were slightly more *accepting/supportive* ($\beta = 0.003$) and exhibited more positive *affect* ($\beta = 0.004$, both $p < 0.001$). *Gender* also had a significant effect, with females reporting slightly higher *acceptance/support* ($\beta = -0.07$) and *affect* ($\beta = -0.11$, both $p < 0.01$) compared to males. Participants' *subjective knowledge* was a significant, yet modest, positive predictor: a one-point increase in the 5-Likert scale of subjective knowledge was associated with a 0.07-point increase in *acceptance/support* ($\beta = 0.07$, $p < 0.001$) and 0.09 in *affect* ($\beta = 0.09$, $p < 0.001$).

4 Discussion

This study aimed to elicit informed levels of *acceptance*, *support*, and *affect* towards four key climate mitigation measures modeled in IAMs: afforestation/reforestation, BECCS, green hydrogen, and sustainable diets. By providing information on the uncertainties surrounding each measure's *geophysical*, *technological*, *economic*, and *social* feasibility and *mitigation potential*, we sought to understand how this type of analytical-factual input reshapes individual judgements and what factors drive these informed evaluations. In doing so, the study revealed four key findings with relevant insights for future modeling in IAMs and climate policy.

First, we found that providing feasibility-related uncertainty information overall had a negative influence on participants' evaluations, reinforcing the importance of eliciting informed—rather than intuitive—views. Before receiving the information, participants had limited awareness of the uncertainties surrounding the feasibility and *mitigation potential of each measure*. Perceptions of uncertainty varied widely between mitigation measures and were often misaligned with scientific estimates, showcasing knowledge gaps. For instance, sustainable diets were perceived as highly uncertain despite receiving comparatively low uncertainty ratings in scientific assessments, while afforestation/reforestation was perceived as less uncertain than experts suggest^{3,7,45}. For all mitigation measures the provision of information increased both *objective knowledge* and *perceived uncertainty*, thus effectively bringing participants' uncertainty perceptions closer to expert assessments, as is the intended objective with informed opinion elicitation¹⁴ (see Supplementary Material A.8 and A.13). For example, the *perceived uncertainty* for afforestation/reforestation rose across all feasibility dimensions, particularly *geophysical* feasibility, while sustainable diets *mitigation potential* was perceived as more certain post information. This new, more accurate understanding of the uncertainties behind the mitigation measure led to a significant decline in *acceptance/support* and, a more modest one, in *affect*. Still, public attitudes remained largely positive, and the relative ranking of measures – with afforestation/reforestation and green hydrogen receiving the highest scores and BECCS and sustainable diets the lowest scores—

remained stable.

Second, the informed evaluations of the mitigation measures align with previous literature, reaffirming a well-established pattern: the public consistently favors nature-based solutions such as afforestation/reforestation over large-scale, engineered technologies like BECCS ^{50,51}. Our results go further, showing that even among participants generally opposed to the mitigation measure, the willingness to support the measure at a higher *mitigation potential* level is higher for afforestation/reforestation than for BECCS. This persistent preference is highly relevant for IAMs, as some IAMs more often rely on large-scale deployment of BECCS rather than afforestation to achieve negative emissions ^{3,52}. Here, our study contributes to the growing literature cautioning against an over-reliance on BECCS by highlighting the trade-off between cost-efficiency and social feasibility risk ⁵³. A mitigation pathway built on a technology like BECCS, which may achieve negative emissions more cost-efficiently but faces lower relative support, will likely face greater implementation barriers than a pathway built on a more popular negative emissions measure like afforestation ⁵². What is more, high social opposition is likely to contain hidden costs due to delays in deployment, and a higher risk of project failure, which can end up distorting the results of cost-optimizing models, unless such disamenity costs or acceptance are directly modelled ^{8,10,54}.

In addition, the low levels of *acceptance/support* and *affect* that we found for sustainable diets are consistent with previous research highlighting the role of cultural norms, policy gaps, and economic barriers in shaping dietary preferences ^{7,55,56}. This pattern was particularly evident in the Netherlands and Poland, where both *acceptance/support* and *affect* fell below the midpoint of the response scale post information. An additional contributing factor may be the high cost of plant-based alternatives, which can be more than 20% higher in price in some regions, such as the Netherlands ⁵⁷. This highlights the need for country-specific research that addresses the socio-economic and cultural obstacles to dietary change, to design more effective and socially acceptable sustainable diet policies. Furthermore, significant and consistent differences in *acceptance* and *affect* between countries that we found—with the Netherlands and Poland, for example, showing lower support for most measures than other countries — underscore that national context is a critical factor. For a unified body like the European Union, which has common climate goals and a collective Nationally Determined Contribution, these divergent national preferences are essential to ensure that strategies are not only effective overall but also acceptable within each country's specific national context.

Third, despite the negative effect of uncertainty information on *acceptance/support* and *affect*, participants remained generally in favor of all mitigation measures. Only 4% of initial supporters shifted to a neutral or opposing stance post-intervention, and most endorsed the highest *mitigation potential* levels for all mitigation measures. One explanation for this resilience lies in the stability of affective responses, which were less sensitive to uncertainty than *acceptance/support*. For instance, analysis of individual emotions showed that hope was expressed positively across all mitigation measures and remained consistently positive and

stable even after the provision of information (Supplementary Material A.9). This suggests that the emotional salience of the measures' climate *mitigation potential* may have outweighed concerns about uncertainties^{30,31}. Moreover, climate change belief emerged as a more powerful predictor of *acceptance/support* and *affect* than any perceived uncertainty dimension, or any of the examined individual or socio-demographic factors. The high levels of belief among participants likely acted as a psychological buffer against the negative effects of the uncertainty^{58–60}. We therefore conclude that, while uncertainty can reduce *acceptance/support*, individuals who hold strong emotions towards mitigation outcomes and climate change beliefs are likely to maintain support or face a lower level of support erosion when learning about the uncertainties involved. This highlights the importance of accounting for affective responses and belief and their evolution in IAMs, as they may offer more stable and predictive insights into real-world public support than cognitive evaluations alone.

Finally, we highlight that among the five uncertainty dimensions, *perceived technological and social uncertainties* were the strongest predictors of *acceptance/support* and *affect*. Notably, the information intervention had a divergent effect: it weakened the influence of *technological uncertainty* on *affect* but amplified the negative effect of *social uncertainty* on *acceptance/support* - particularly for BECCS and sustainable diets. While prior work indicates that belief in collective compliance is a crucial prerequisite for individual policy support^{61–63}, our results further demonstrate that providing information on social uncertainties can actively amplify this barrier, further decreasing the likelihood of acceptance. It also underscores that for policies to succeed, they must not only be technically sound but also be perceived as socially and politically viable, a perception heavily influenced by political signals and perceived public consensus^{64,65}.

This study has several limitations that could be addressed in future research. First, our pre-post design only captured the immediate effects of the information intervention, but it cannot assess the long-term stability of these informed attitudes. Previous studies have shown that informed attitudes often experience a rebound effect, gradually returning to initial attitudes over time^{21,66}. Future longitudinal research could determine whether the observed shifts in perception and the stabilization of attitudes persist over time. Second, our results are based on information that only addresses uncertainties associated with each measure's feasibility and potential. We did not, however, provide detailed, countervailing information on their specific co-benefits, trade-offs, or potential risks, which are also important aspects when forming informed and rational decisions²⁶. Third, we used a between-subjects design, where each participant evaluated only one mitigation measure, due to concerns about survey length. This approach does not replicate real-world scenarios where citizens and policymakers must often choose or prioritize among a portfolio of competing options^{9,29}. A final methodological limitation is the one-way nature of our analysis. Our study provides food for thought for IAM, but it does not feature a direct, iterative integration with them¹¹. A truly coupled approach would involve a two-way, dynamic feedback loop, where public attitudes and feasibility uncertainty constraints



identified in our surveys could be used to adjust the assumptions within IAMs. The model would then generate new, potentially more socially realistic pathways, which could, in turn, be presented back to the public for further evaluation. This dynamic coupling would likely produce more robust and socially acceptable climate pathways than either discipline can achieve in isolation.

5 Conclusions

This study provides a cross-country analysis of informed public evaluations of four uncertain climate mitigation measures modeled in IAMs: afforestation/reforestation, BECCS, green hydrogen, and sustainable diets. Our results first demonstrate that providing information on feasibility-related uncertainties successfully creates a more informed public, which, while more aware of the challenges, remains broadly accepting/supportive of climate action. While cognitive acceptance and support are more sensitive to uncertainty information, affective responses remain comparatively stable. This stability is reflected in a consistent order of preferences, with afforestation/reforestation consistently favored over green hydrogen, BECCS, and sustainable diets. We also identified significant country-specific differences: the Netherlands and Poland report notably lower acceptance levels, particularly for sustainable diets, where support fell below the midpoint. Our models confirm that perceived uncertainty is a key driver of opposition, with technological and social uncertainties standing out as the most influential among the feasibility dimensions. Finally, the strongest factor predicting public support is individuals' climate change beliefs. Higher levels of subjective knowledge and trust in climate scientists are also positively associated with acceptance/support and affect. In contrast, political trust has a marginal negative effect, while socio-demographic factors have little to no influence on participants' attitudes. To enhance quality and relevance, IAMs should hence account for both the variability of public acceptance and affect across mitigation measures and countries, ideally engaging in a two-way dynamic feedback loop. Addressing social feasibility concerns and aligning policies with public values will be critical for building effective and socially accepted climate policies.

6 Acknowledgements

This work received funding from the Swiss State Secretariat for Education, Research, and Innovation SEFRI for the project PRISMA “Net zero pathway research through integrated assessment model advancements” (project no. 101081604) and from the Swiss Federal Office of Energy (SFOE) as part of the SWEET project PATHFINDER. The authors thank PRISMA experts, colleagues from University of Geneva's Renewable Energy Systems group, Joanna Sobocińska, Marta Brucka, Mellano Océane, and Francesco Sasso for the translation and revision of the technical information used for this project. Manuscript review by Johannes Emmerling is highly appreciated, too. The authors bear sole responsibility for the conclusions and the results.



7 CRediT authorship contribution statement

Valeria Sorgato: Conceptualization, Methodology, Data curation, Formal analysis, Visualization, Writing – original draft, Writing – review & editing.

Morris Krainz: Conceptualization, Methodology, Writing – review & editing.

Tobias Brosch: Conceptualization, Writing – review & editing.

Evelina Trutnevyte: Conceptualization, Funding acquisition, Methodology, Supervision, Writing – review & editing.

8 Funding sources

This work received funding from the Swiss State Secretariat for Education, Research, and Innovation SEFRI for the project PRISMA “Net zero pathway research through integrated assessment model advancements” (project no. 101081604) and from the Swiss Federal Office of Energy (SFOE) as part of the SWEET project PATHFINDER. The authors bear sole responsibility for the conclusions and the results.

9 Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the first author used Chat GPT and Claude in order to improve the readability and language of the work. After using this tool, the first author reviewed and edited the content as needed and takes full responsibility for the content of the published article.

10 References

1. Huijts NMA, Molin EJE, Steg L. Psychological factors influencing sustainable energy technology acceptance: A review-based comprehensive framework. *Renew Sustain Energy Rev.* 2012;16(1):525-531. doi:10.1016/j.rser.2011.08.018
2. Emodi N, Lovell H, Levitt C, Franklin E. A systematic literature review of societal acceptance and stakeholders’ perception of hydrogen technologies. *Int J Hydrog Energy.* 2021;46. doi:10.1016/j.ijhydene.2021.06.212
3. IPCC. *Working Group III Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change.*; 2022. <https://www.ipcc.ch/report/ar6/wg3/>
4. Bellamy R, Lezaun J, Palmer J. Perceptions of bioenergy with carbon capture and storage in different policy scenarios. *Nat Commun.* 2019;10(1):743. doi:10.1038/s41467-019-08592-5
5. Buchner J, Menrad K, Decker T. Public acceptance of green hydrogen production in Germany. *Renew Sustain Energy Rev.* 2025;208:115057. doi:10.1016/j.rser.2024.115057



6. Hartmann C, Siegrist M. Consumer perception and behaviour regarding sustainable protein consumption: A systematic review. *Trends Food Sci Technol.* 2017;61. doi:10.1016/j.tifs.2016.12.006
7. Johnston JL, Fanzo JC, Cogill B. Understanding Sustainable Diets: A Descriptive Analysis of the Determinants and Processes That Influence Diets and Their Impact on Health, Food Security, and Environmental Sustainability¹²³. *Adv Nutr.* 2014;5(4):418-429. doi:10.3945/an.113.005553
8. Fisch-Romito V, Jaxa-Rozen M, Wen X, Trutnevyte E. Multi-country evidence on societal factors to include in energy transition modelling. *Nat Energy.* 2025;10(4):460-469. doi:10.1038/s41560-025-01719-7
9. Xexakis G, Hansmann R, Volken SP, Trutnevyte E. Models on the wrong track: Model-based electricity supply scenarios in Switzerland are not aligned with the perspectives of energy experts and the public. *Renew Sustain Energy Rev.* 2020;134:110297. doi:10.1016/j.rser.2020.110297
10. Wen X, Gonzalez Contreras J, Stadelmann-Steffen I, Sasse JP, Trutnevyte E. High Sensitivity to Methodological Choices When Integrating Social Acceptance Data in Electricity System Modeling. Published online November 20, 2024. doi:10.2139/ssrn.5027456
11. Trutnevyte E, Hirt LF, Bauer N, et al. Societal Transformations in Models for Energy and Climate Policy: The Ambitious Next Step. *One Earth.* 2019;1(4):423-433. doi:10.1016/j.oneear.2019.12.002
12. Odenweller A, Ueckerdt F, Nemet GF, Jensterle M, Luderer G. Probabilistic feasibility space of scaling up green hydrogen supply. *Nat Energy.* 2022;7(9):854-865. doi:10.1038/s41560-022-01097-4
13. Dietz T, Stern PC. *New Tools for Environmental Protection: Education, Information and Voluntary Measures.* Vol 6. NATIONAL ACADEMY PRESS; 2003. Accessed August 7, 2025. <https://linkinghub.elsevier.com/retrieve/pii/S146290110300073X>
14. Wong-Parodi G, Krishnamurti T, Davis A, Schwartz D, Fischhoff B. A decision science approach for integrating social science in climate and energy solutions. *Nat Clim Change.* 2016;6(6):563-569. doi:10.1038/nclimate2917
15. Dechezleprêtre A, Fabre A, Kruse T, Planterose B, Chico AS, Stantcheva S. Fighting Climate Change: International Attitudes Toward Climate Policies. Published online July 2022:w30265. doi:10.3386/w30265
16. Smith EK, Mlakar Ž, Levis A, et al. Six Faces of Climate Policy Support in the EU. *Six Faces Clim Policy Support EU.* Published online April 9, 2025. doi:10.31219/osf.io/pnvw8_v1
17. Edwards W. THE THEORY OF DECISION MAKING.
18. Yates JF. *Judgment and Decision Making.* Prentice-Hall, Inc; 1990:xvi, 430.



19. Fleishman LA, De Bruin WB, Morgan MG. Informed public preferences for electricity portfolios with CCS and other low-carbon technologies. *Risk Anal Off Publ Soc Risk Anal.* 2010;30(9):1399-1410. doi:10.1111/j.1539-6924.2010.01436.x
20. Brückmann G. Test-drives & information might not boost actual battery electric vehicle uptake? *Transp Res Part Policy Pract.* 2022;160:204-218. doi:10.1016/j.tra.2022.03.025
21. Volken S, Xexakis G, Trutnevyte E. Perspectives of Informed Citizen Panel on Low-Carbon Electricity Portfolios in Switzerland and Longer-Term Evaluation of Informational Materials. *Environ Sci Technol.* 2018;52. doi:10.1021/acs.est.8b01265
22. Bles AM van der, Linden S van der, Freeman ALJ, Spiegelhalter DJ. The effects of communicating uncertainty on public trust in facts and numbers. *Proc Natl Acad Sci U S A.* 2020;117(14):7672. doi:10.1073/pnas.1913678117
23. Gao L, Jiang J, He H, Zhou Q, Wang S, Li J. Uncertainty or trust? Political trust, perceived uncertainty and public acceptance of personal carbon trading policy. *Environ Geochem Health.* 2022;44(9):3157-3171. doi:10.1007/s10653-022-01214-y
24. Wei H, Xianjun D, Khan K. The race to zero emission: Can climate policy uncertainty threaten decarbonization? *Environ Dev Sustain.* Published online July 2, 2024. doi:10.1007/s10668-024-05118-y
25. Bostrom A, Böhm G, O'Connor RE. Targeting and tailoring climate change communications. *WIREs Clim Change.* 2013;4(5):447-455. doi:10.1002/wcc.234
26. Patt AG, Weber EU. Perceptions and communication strategies for the many uncertainties relevant for climate policy. *WIREs Clim Change.* 2014;5(2):219-232. doi:10.1002/wcc.259
27. Steg L, Veldstra J, De Kleijne K, et al. A method to identify barriers to and enablers of implementing climate change mitigation options. *One Earth.* 2022;5(11):1216-1227. doi:10.1016/j.oneear.2022.10.007
28. Peters E, Västfjäll D, Gärling T, Slovic P. Affect and Decision Making: A “Hot” Topic. *J Behav Decis Mak.* 2006;19(2):79-85. doi:10.1002/bdm.528
29. Klaus G, Ernst A, Oswald L. Psychological factors influencing laypersons’ acceptance of climate engineering, climate change mitigation and business as usual scenarios. *Technol Soc.* 2020;60:101222. doi:10.1016/j.techsoc.2019.101222
30. Loewenstein G, Weber E, Hsee C, Welch N. Risk As Feelings. *Psychol Bull.* 2001;127:267-286. doi:10.1037/0033-2909.127.2.267
31. Rottenstreich Y, Hsee CK. Money, kisses, and electric shocks: on the affective psychology of risk. *Psychol Sci.* 2001;12(3):185-190. doi:10.1111/1467-9280.00334
32. *Annual European Union Greenhouse Gas Inventory 1990– 2023 and Inventory Document 2025.* European Commission, DG Climate Action European Environment Agency; 2025. Accessed June 30, 2025. <https://www.eea.europa.eu/en/analysis/publications/annual->



33. van Valkengoed AM, Steg L, Perlaviciute G. Development and validation of a climate change perceptions scale. *J Environ Psychol.* 2021;76:101652. doi:10.1016/j.jenvp.2021.101652
34. Krainz M, Sorgato V, Vallaes I, Trutnevyte E, Brosch T. From Surveys to the Ballot Box: Identifying and validating the strongest predictors of Renewable Energy Policy Support Across Europe. *Press.* Published online 2025.
35. Spampatti T, Brosch T, Trutnevyte E, Hahnel UJJ. A Preregistered Field Study of the Trust Inoculation Against a Negative Event Involving Geothermal Energy Systems. Molho C, ed. *Collabra Psychol.* 2023;9(1):89755. doi:10.1525/collabra.98755
36. Gaziano C, McGrath K. Measuring the Concept of Credibility. *Journalism Quarterly.* Published online 1986. doi:10.1177/107769908606300301
37. Kyselá E, Ščasný M, Zvěřinová I. Attitudes toward climate change mitigation policies: a review of measures and a construct of policy attitudes. *Clim Policy.* 2019;19(7):878-892. doi:10.1080/14693062.2019.1611534
38. Spampatti T, Hahnel UJJ, Trutnevyte E, Brosch T. Short and long-term dominance of negative information in shaping public energy perceptions: The case of shallow geothermal systems. *Energy Policy.* 2022;167:113070. doi:10.1016/j.enpol.2022.113070
39. Hydrogen. Accessed September 16, 2024. <https://www.irena.org/Energy-Transition/Technology/Hydrogen>
40. Ingaldi M, Klimecka-Tatar D. People's Attitude to Energy from Hydrogen—From the Point of View of Modern Energy Technologies and Social Responsibility. *Energies.* 2020;13(24):6495. doi:10.3390/en13246495
41. Liang S, Ziegler AD, Reich PB, et al. Climate mitigation potential for targeted forestation after considering climate change, fires, and albedo. *Sci Adv.* 2025;11(15):eadn7915. doi:10.1126/sciadv.adn7915
42. Lefvert A. *On the Potential Deployment of Bioenergy with Carbon Capture and Storage (BECCS) in Sweden.* KTH Royal Institute of Technology; 2024.
43. IPCC WGIII report: Bioenergy with carbon capture and storage (BECCS). Zero Carbon Analytics. Accessed July 3, 2025. <https://zerocarbon-analytics.org/archives/food/ipcc-working-group-iii-report-bioenergy-with-carbon-capture-and-storage-beccs>
44. Net Zero by 2050 – Analysis - IEA. Accessed July 3, 2025. <https://www.iea.org/reports/net-zero-by-2050>
45. Wageningen U. The world can be fed with only plant-based food. WUR. June 21, 2022. Accessed July 3, 2025. <https://www.wur.nl/en/newsarticle/the-world-can-be-fed-with-only-plant-based-food.htm>

46. Faul F, Erdfelder E, Lang AG, Buchner A. G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behav Res Methods*. 2007;39(2):175-191. doi:10.3758/BF03193146
47. Shaw M, Rights JD, Sterba SS, Flake JK. r2mlm: An R package calculating R-squared measures for multilevel models. *Behav Res Methods*. 2023;55(4):1942-1964. doi:10.3758/s13428-022-01841-4
48. Swim JK, Guerriero JG, Gasper K, DeCoster J, Lengieza ML. Emotions and policy information predicting water-quality policy support. *J Environ Psychol*. 2024;98:102385. doi:10.1016/j.jenvp.2024.102385
49. Prinzing M. Proenvironmental Behavior Increases Subjective Well-Being: Evidence From an Experience-Sampling Study and a Randomized Experiment. *Psychol Sci*. 2024;35(9):951-961. doi:10.1177/09567976241251766
50. Merk C, Liebe U, Meyerhoff J, Rehdanz K. German citizens' preference for domestic carbon dioxide removal by afforestation is incompatible with national removal potential. *Commun Earth Environ*. 2023;4(1):1-9. doi:10.1038/s43247-023-00713-9
51. Hynek N, Gavurova B, Moravec V, Kubak M. Nature-based and geo-engineering climate mitigation technologies: Public acceptance and security prospects. *iScience*. 2025;28(5):112303. doi:10.1016/j.isci.2025.112303
52. Köberle AC. The Value of BECCS in IAMs: a Review. *Curr Sustain Energy Rep*. 2019;6(4):107-115. doi:10.1007/s40518-019-00142-3
53. Fuss S, Canadell JG, Peters GP, et al. Betting on negative emissions. *Nat Clim Change*. 2014;4(10):850-853. doi:10.1038/nclimate2392
54. Ruhnau O, Eicke A, Sgarlato R, Tröndle T, Hirth L. Cost-Potential Curves of Onshore Wind Energy: the Role of Disamenity Costs. *Environ Resour Econ*. 2024;87(2):347-368. doi:10.1007/s10640-022-00746-2
55. Principato L, Pice G, Pezzi A. Understanding food choices in sustainable healthy diets – A systematic literature review on behavioral drivers and barriers. *Environ Sci Policy*. 2025;163:103975. doi:10.1016/j.envsci.2024.103975
56. Halicka E, Kaczorowska J, Rejman K, Szczybyło A. Parental Food Choices and Engagement in Raising Children's Awareness of Sustainable Behaviors in Urban Poland. *Int J Environ Res Public Health*. 2021;18(6):3225. doi:10.3390/ijerph18063225
57. Hoenink JC, Waterlander W, Vandevijvere S, Beulens JWJ, Mackenbach JD. The cost of healthy versus current diets in the Netherlands for households with a low, middle and high education. *SSM - Popul Health*. 2022;20:101296. doi:10.1016/j.ssmph.2022.101296
58. Bertolotti M, Catellani P, Nelson T. Framing Messages on the Economic Impact of Climate Change Policies: Effects on Climate Believers and Climate Skeptics. *Environ Commun*. 2021;15(6):715-730. doi:10.1080/17524032.2021.1890175



59. Hurst Loo AM, Walker BR. Climate change knowledge influences attitude to mitigation via efficacy beliefs. *Risk Anal Off Publ Soc Risk Anal*. 2023;43(6):1162-1173. doi:10.1111/risa.14026
60. Wendling ZA, Attari SZ, Carley SR, et al. On the Importance of Strengthening Moderate Beliefs in Climate Science to Foster Support for Immediate Action. *Sustainability*. 2013;5(12):5153-5170. doi:10.3390/su5125153
61. Nilsson A, Von Borgstede C, Biel A. Willingness to accept climate change strategies: The effect of values and norms. *J Environ Psychol*. 2004;24(3):267-277. doi:10.1016/j.jenvp.2004.06.002
62. Sparkman G, Howe L, Walton G. How social norms are often a barrier to addressing climate change but can be part of the solution. *Behav Public Policy*. 2021;5(4):528-555. doi:10.1017/bpp.2020.42
63. Sherman DK, Updegraff JA, Handy MS, Eom K, Kim HS. Beliefs and Social Norms as Precursors of Environmental Support: The Joint Influence of Collectivism and Socioeconomic Status. *Pers Soc Psychol Bull*. 2022;48(3):463-477. doi:10.1177/01461672211007252
64. McCright AM, Dunlap RE, Xiao C. Increasing Influence of Party Identification on Perceived Scientific Agreement and Support for Government Action on Climate Change in the United States, 2006–12. Published online April 1, 2014. doi:10.1175/WCAS-D-13-00058.1
65. Stadelmann-Steffen I. Citizens as veto players: climate change policy and the constraints of direct democracy. *Environmental Politics*. Vol 20, No 4. Accessed July 7, 2025. <https://doi.org/10.1080/09644016.2011.589577>
66. Kunas S, Trutnevyte E. Informed minds, opinions aligned? Informed perceptions towards solar PV locations in Switzerland. *Environ Res Commun*. Published online 2025. doi:10.1088/2515-7620/adf0cc



Supplementary Material

Acceptance of highly uncertain climate change mitigation measures by informed European citizens: implications for modeling

Authors: **Valeria SORGATO^{1*}**, **Morris Krainz²**, **Tobias Brosch²**, **Evelina Trutnevyte¹**

¹ Renewable Energy Systems, Institute for Environmental Sciences (ISE), Section of Earth and Environmental Sciences, University of Geneva, Switzerland

² Consumer Decision & Sustainable Behavior Lab, Department of Psychology, Faculty of Psychology and Educational Sciences (FPSE), University of Geneva, Switzerland

* Corresponding author (Uni Carl Vogt, Boulevard Carl Vogt 66, CH-1211 Geneva 4, Switzerland; +41 22 3791251; valeria.sorgato@unige.ch)

Table of Contents

A1. Survey structure	35
A2. Survey in English	36
A3. Sample characteristics	57
A.4 Statistical analysis	58
A.5 Objective knowledge	59
A.6 Initial and Informed affect across mitigation measures, and country	60
A.7 Support for mitigation potential levels	61
A.8 Initial and informed perceived uncertainty across dimensions and mitigation measures	63
A.9 Initial and informed mean emotional responses across mitigation measures ...	64
A.10. Effect of perceived uncertainty: multilevel model between and within effects	65
A.11 Impact of information on the effect of perceived uncertainty	71
A.12 Fixed effect estimates from multilevel mixed models predicting acceptance and affect	74
A.13. Initial and informed evaluations and the effect of perceived uncertainty, across mitigation measures	79



A1. Survey structure

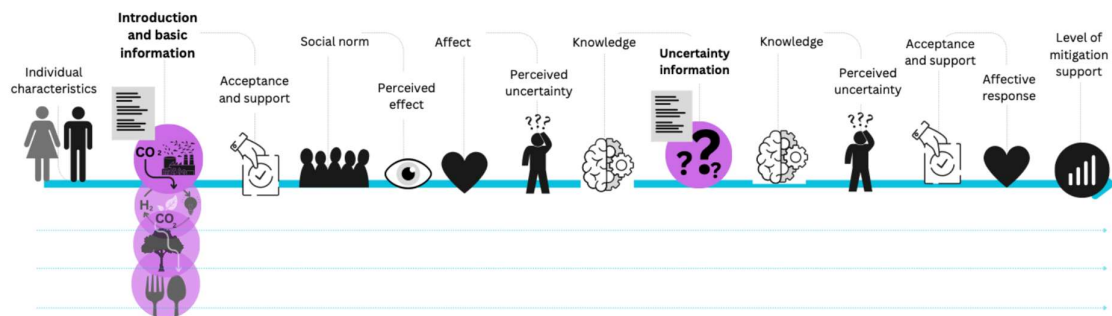


Figure 5. Survey structure: The flow of questions in the survey is illustrated from left to right. Participants were randomly assigned to one of four conditions, each focused on a single mitigation measure—BECCS, green hydrogen, afforestation and reforestation, or shifting toward sustainable diets. The two purple icons indicate key moments in the survey where information was delivered: (1) general information about the assigned mitigation measure, and (2) detailed, neutral information on the uncertainties surrounding its mitigation potential and four feasibility dimensions. For the purpose of this study, we did not consider social norms and perceived effect responses.

A2. Survey in English

Age

How old are you?

Gender

What is your gender?

- Female
- Male
- Other

Education

What is your level of education?

- Compulsory school (primary and lower secondary education)
- Secondary level (upper secondary education and post-secondary non-tertiary education e.g. university entrance certificates for adults or non-tertiary vocational education after general upper secondary)
- Tertiary level (all university and vocational college education, including PhD/doctorate and equivalent)
- Prefer not to answer

Income

Please select your monthly net income (after taxes):

- ≤ 3.000 EUR
- 3.001 - 6.000 EUR
- 6.001 - 16.000 EUR
- >16.000 EUR
- I prefer not to answer

Mitigation information

In this survey the words “**climate change mitigation**” and “**mitigation measure**” will appear very often. When we talk about “**climate change mitigation**,” we refer to the actions that we can take to reduce or prevent greenhouse gas emissions (such as carbon dioxide or methane) from entering the atmosphere. This helps limit the rise in global temperature and its associated impacts, such as extreme heat, droughts, or flooding. “**Mitigation measures**” are the specific actions that help reduce or prevent greenhouse gas emissions in the atmosphere.

These range from individual choices, such as eating less meat, to large-scale institutional efforts, like building solar panel systems to generate renewable energy. Now that these concepts are clear, you're ready to continue with the survey!

Climate change beliefs

How much do you agree with the following statements?
(-3 Strongly disagree to +3 Strongly agree)

- I believe that climate change is real
- The main causes of climate change are human activities
- The main causes of climate change are human activities
- Climate change will bring about serious negative consequences
- My local area will be influenced by climate change
- I worry about the impacts of climate change
- It will be a long time before the consequences of climate change are felt
- I feel that it is my personal obligation to take steps toward mitigating climate change
- People like me should do whatever they can to mitigate climate change

Political trust

How much do you agree with the following statements?
(-3 Strongly disagree to +3 Strongly agree)

- My personal values align with the values of my country's current government
- With respect to climate change mitigation and protecting the environment, I feel my country's current government shares similar interests as me
- When my country's current government claims to do everything to minimize the risks for me as a citizen, I believe them
- My country's current government is trustworthy in terms of climate change mitigation and safety
- My country's current government is competent when it comes to climate change mitigation
- My country's current government has the necessary expertise to make the right decisions when it comes to climate change mitigation

Trust in climate scientists

How much do you agree with the following statement?
 (-3 Strongly disagree to +3 Strongly agree)

- Scientists are biased when it comes to climate change
- Scientists do not tell the whole story when it comes to climate change
- The results reported by climate change scientists are accurate
- Climate change scientists do not separate facts from opinions when reporting their results
- Climate change scientists can be trusted
- Climate change scientists tend to be sensationalist

In questionnaires like ours, there are sometimes participants who don't read the questions carefully and just click through the survey quickly. This means that there are a lot of random answers that affect the results of research studies. To show that you read our questions carefully, please enter 'Gray' as your answer to the next question. What is your favorite colour?

- Red
- Green
- Gray
- Yellow
- Black
- Blue

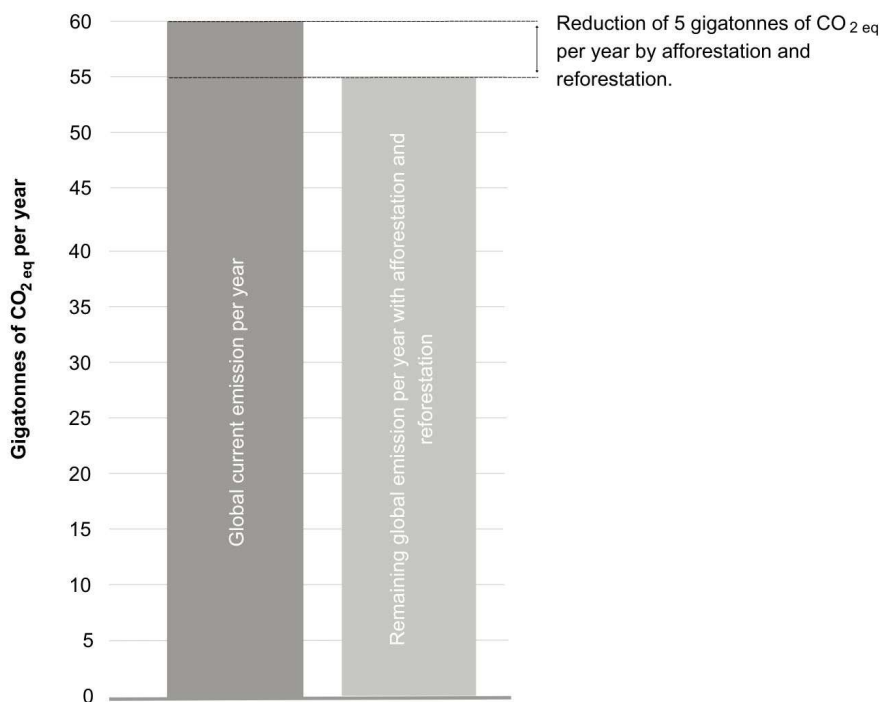
Subjective Knowledge

In this study, we are interested in learning about your opinion regarding **\$(e://Field/Condition)** as a climate change mitigation measure. Before starting: Can you please rate your knowledge regarding **\$(e://Field/Condition)** as a climate change mitigation measure? (For example: do you know what it is, how it works, and why is it considered a climate change

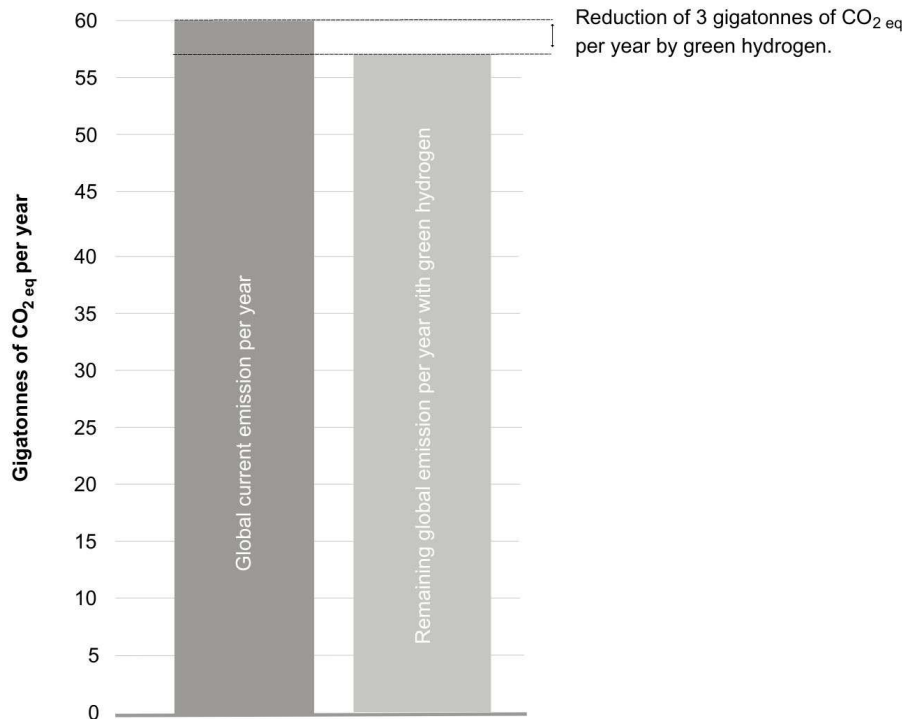
mitigation measure)

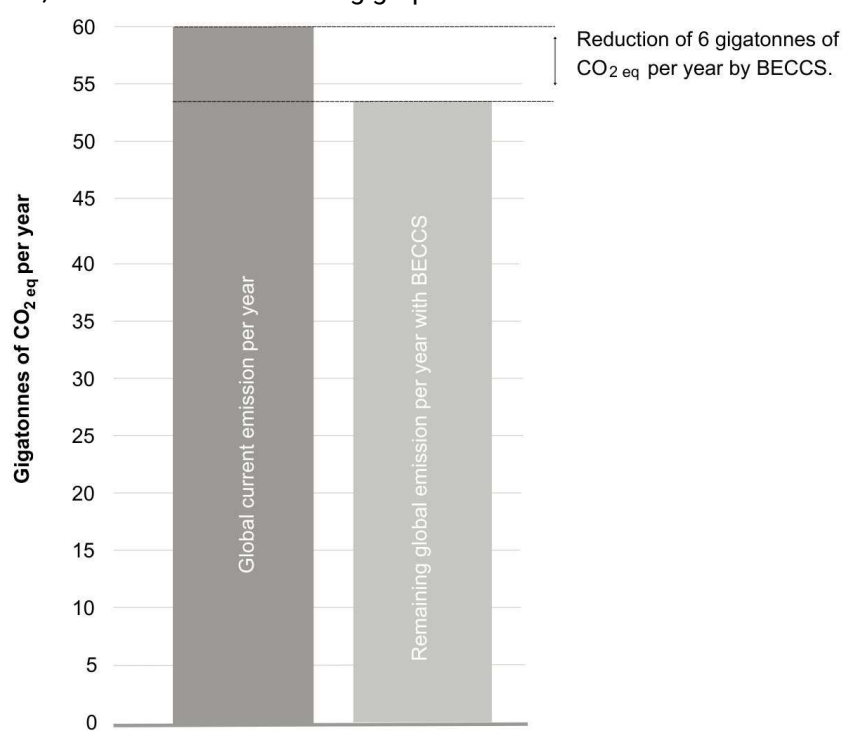
- No knowledge
- Little knowledge
- Moderate knowledge
- Good knowledge
- Very good knowledge

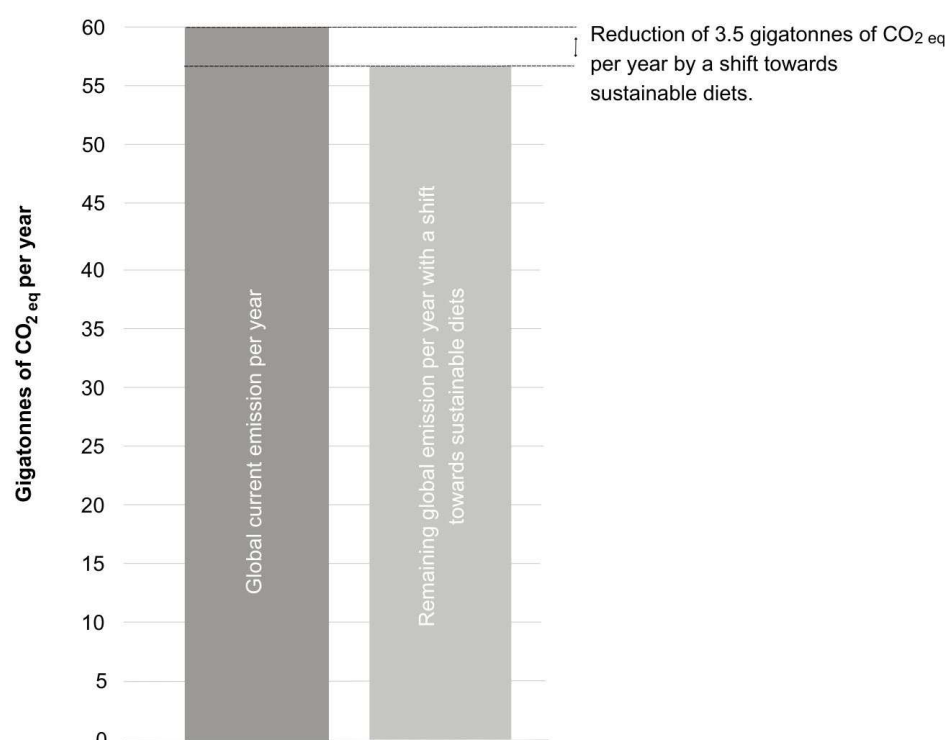


General Information:									
Introductory paragraph for all mitigation measures	The Intergovernmental Panel on Climate Change (IPCC), an international body of scientists, warns that if human activities continue at the current rate, global temperature will rise to unsafe levels before 2100. The main drivers of global warming are greenhouse gases—gases in the atmosphere that trap heat, such as carbon dioxide and methane—released by human activities. Currently, the world emits about 60 gigatons of greenhouse gases per year, measured as carbon dioxide equivalent (CO₂eq). To limit temperature rise, we must achieve net-zero greenhouse gas emissions by 2050. This requires using various mitigation measures, including \$(e://Field/Condition)								
Afforestation/ reforestation	Afforestation involves planting trees in areas that do not have natural forest. Reforestation involves planting trees in areas where forests have been depleted or degraded. Both these processes help capture carbon dioxide (CO₂) from the atmosphere as trees naturally absorb CO₂ during photosynthesis, storing carbon in their biomass and the soil. The IPCC has calculated the global mitigation potential of afforestation and reforestation, that is, the amount of greenhouse gases emissions (CO₂eq) that afforestation and reforestation could remove from the atmosphere if implemented worldwide. According to the IPCC, afforestation and reforestation could globally remove 5 gigatons of CO₂eq emissions per year from 2020 to 2050, as shown in the following graph.  The bar chart displays two vertical bars. The first bar, labeled 'Global current emission per year', reaches the 60 mark on the y-axis. The second bar, labeled 'Remaining global emission per year with afforestation and reforestation', reaches the 55 mark. A bracket between the tops of the two bars indicates a 'Reduction of 5 gigatonnes of CO₂ eq per year by afforestation and reforestation.' <table border="1"> <thead> <tr> <th>Category</th> <th>Emissions (Gigatonnes of CO₂eq per year)</th> </tr> </thead> <tbody> <tr> <td>Global current emission per year</td> <td>60</td> </tr> <tr> <td>Remaining global emission per year with afforestation and reforestation</td> <td>55</td> </tr> <tr> <td>Reduction</td> <td>5</td> </tr> </tbody> </table>	Category	Emissions (Gigatonnes of CO ₂ eq per year)	Global current emission per year	60	Remaining global emission per year with afforestation and reforestation	55	Reduction	5
Category	Emissions (Gigatonnes of CO ₂ eq per year)								
Global current emission per year	60								
Remaining global emission per year with afforestation and reforestation	55								
Reduction	5								

Green hydrogen	Green hydrogen consists of splitting water (H₂O) into oxygen (O) and hydrogen (H) using electricity generated from renewable sources like wind or solar power. Therefore, green hydrogen production does not result in carbon dioxide (CO₂) emissions. Hydrogen can then be used as a fuel to store and provide energy to sectors that are difficult to decarbonize through electrification, such as industry, buildings, and transportation. The IPCC has calculated the global mitigation potential of green hydrogen, that is, the amount of greenhouse gases emissions (CO₂eq) that green hydrogen could avoid if implemented worldwide. According to the IPCC, green hydrogen could globally reduce 3 gigatons of CO₂eq per year from 2020 to 2050, as shown in the following graph.
----------------	--



BECCS	BECCS involves growing plants, such as grains and sugarcane, that capture large amounts of carbon dioxide (CO₂) from the atmosphere. These plants are then burned to produce energy. However, during combustion, the CO₂ inside the plants would not be emitted into the atmosphere but would be technically captured and deposited underground in the deep rocks, hence reducing the amount of CO₂ in the atmosphere. The IPCC has calculated the global mitigation potential of BECCS, that is, the amount of greenhouse gases emissions (CO₂eq) that BECCS could avoid and removed from the atmosphere if implemented worldwide. According to the IPCC, BECCS could globally reduce 6 gigatonnes of CO₂eq per year from 2020 to 2050, as shown in the following graph.  <table border="1"> <thead> <tr> <th>Category</th> <th>Gigatonnes of CO₂eq per year</th> </tr> </thead> <tbody> <tr> <td>Global current emission per year</td> <td>60</td> </tr> <tr> <td>Remaining global emission per year with BECCS</td> <td>54</td> </tr> </tbody> </table>	Category	Gigatonnes of CO ₂ eq per year	Global current emission per year	60	Remaining global emission per year with BECCS	54
Category	Gigatonnes of CO ₂ eq per year						
Global current emission per year	60						
Remaining global emission per year with BECCS	54						

Sustainable diets	Sustainable diets consist of eating more protein from plants than from animals. Shifting towards diets with more plant-based proteins and fewer animal products, particularly red meat, can reduce carbon dioxide (CO₂) and other greenhouse gas emissions. This is because plant-based diets require much less land than animal products, lowering CO₂ emissions from the conversion of forests to agricultural land for livestock feed and grazing. Additionally, cattle naturally produce large amounts of methane (another greenhouse gas) during digestion, which cannot be significantly reduced by farming practices alone. The IPCC has calculated the global mitigation potential of shifting towards sustainable diets, that is, the amount of greenhouse gases emissions (CO₂eq) that shifting towards sustainable diets could avoid if implemented worldwide. According to the IPCC, shifting towards sustainable diets could globally reduce 3.5 gigatons of CO₂eq emissions per year from 2020 to 2050, as shown in the following graph.  <table border="1"> <thead> <tr> <th>Category</th> <th>Gigatonnes of CO₂ eq per year</th> </tr> </thead> <tbody> <tr> <td>Global current emission per year</td> <td>60</td> </tr> <tr> <td>Remaining global emission per year with a shift towards sustainable diets</td> <td>56.5</td> </tr> </tbody> </table>	Category	Gigatonnes of CO ₂ eq per year	Global current emission per year	60	Remaining global emission per year with a shift towards sustainable diets	56.5
Category	Gigatonnes of CO ₂ eq per year						
Global current emission per year	60						
Remaining global emission per year with a shift towards sustainable diets	56.5						

Attention check

Afforestation/reforestation

Based on the text that you have just read please indicate if the following statement is true, false or if you don't know.

Afforestation involves planting trees in areas that do not have natural forest.

True. False

Green hydrogen:

Based on the text that you have just read please indicate if the following statement is true, false or if you don't know.

Green hydrogen is produced with renewable energy such as solar or wind power.

True False

BECCS:

Based on the text that you have just read please indicate if the following statement is true, false or if you don't know.

Bioenergy with carbon capture and storage (BECCS) captures CO₂ directly from the atmosphere and stores it underground without involving plant growth or combustion.

True False

Sustainable diets:

Based on the text that you have just read please indicate if the following statement is true, false or if you don't know.

Sustainable diets consist more of eating animal protein than plant protein

True. False

Acceptance

Please indicate your opinion regarding $\{e://Field/Condition\}$:

How acceptable do you find this mitigation measure?

(-3 Totally unacceptable to +3 Totally acceptable)

To what extent are you in favor or against this mitigation measure

(-3 Completely against to +3 Completely in favor)

To what extent do you agree with the implementation of this mitigation measure?

(-3 Strongly disagree to +3 Strongly agree)

Would you rather have the government introduce this mitigation measure or not?
(-3 Strongly prefer NOT to introduce to +3 Strongly prefer to introduce)

Support

There are different ways of expressing support for or opposition to climate change mitigation measures. Which behaviors would you rather adopt regarding $\{e://Field/Condition\}$ if it



were implemented in [COUNTRY]?

Voice a...

- ...very negative opinion to friends and/or family (1)
- ...negative opinion to friends and/or family (2)
- ...rather negative opinion to friends and/or family (3)
- ... rather positive opinion to friends and/or family (4)
- ... positive opinion to friends and/or family (5)
- ... very positive opinion to friends and/or family (6)
- Not voice an opinion

I would...

- ...definitely sign a petition against it (1)
- ...sign a petition against it (2)
- ...rather sign a petition against it (3)
- ...rather sign a petition in favor of it (4)
- ...sign a petition in favor of it (5)
- ...definitely sign a petition in favor of it (6)
- Not sign a petition

Contact a representative to voice a ...

- ...very negative opinion (1)
- ...negative opinion (2)
- ... rather negative opinion (3)
- ... rather positive opinion (4)
- ...positive opinion (5)
- ...very positive opinion (6)
- Not contact a representative

In a direct public vote...

- ...definitely vote against it (1)
- ...vote against it (2)
- ...somewhat vote against it (3)
- ...somewhat vote in favor of it (4)
- ...vote in favor of it (5)
- ...definitely vote in favor of it (6)
- Not vote

Static norms

What do you think is the percentage of the population that would...

0 25 50 75 100

... accept the implementation of this mitigation measure.	
... openly support the implementation of this mitigation measure (e.g. voice a positive opinion or vote in favour of it).	

Dynamic norms

How do you think the opinion of the population regarding $\{e://Field/Condition\}$ will develop in the next 12 months?

In the next 12 months, the number of people in [COUNTRY] who would...

...**accept the implementation of this mitigation measure will...**

- ...decrease strongly (1)
- ...decrease (2)
- ...rather decrease (3)
- ...neither decrease nor increase (4)
- ... rather increase (5)
- ...increase (6)
- ...increase strongly (7)

...**openly support the implementation of** this mitigation measure (e.g. voice a positive opinion or vote in favor of it), will...

- ...decrease strongly (1)
- ...decrease (2)
- ... rather decrease (3)
- ...neither decrease nor increase (4)
- ...rather increase (5)
- ...increase (6)
- ...increase strongly (7)

Environmental effects

Please rate how you think **\$(e://Field/Condition)** will affect **the environment**.

Overall, **\$(e://Field/Condition)** will...
(-3 *Strongly disagree* to +3 *Strongly agree*)

- ...be beneficial for the environment
- ...be harmful for the environment.
- ...help mitigate climate change.

Social effects

Please rate how you think **\$(e://Field/Condition)** will affect **the society**.
(-3 *Strongly disagree* to +3 *Strongly agree*)

Overall, **\$(e://Field/Condition)** will...

- ...be beneficial for the society and people.
- ...be harmful for the society and people

Person effect

Please rate how you think **\$(e://Field/Condition)** will affect **you personally**.

- Do you think that your household would win or lose financially from this mitigation measure?
- Overall, implementing this mitigation measure would be ___ towards me.
- Overall, this mitigation measure will have ___ on my comfort.

Different groups effect

Please rate how you think **\$(e://Field/Condition)** will affect **different groups of people**.

- In your view, would the low-income earners win or lose if this mitigation measure was implemented in [COUNTRY]?
- Overall, this mitigation measure is ___ towards people in [COUNTRY]
- Overall, this mitigation measure is ___ towards people in other countries

Affect

In general, how do you feel regarding $\{e://Field/Condition\}$?

- very negatively (1)
- negatively (2)
- somewhat negatively (3)
- neither negatively nor positively (4)
- somewhat positively (5)
- positively (6)
- very positively (7)

Emotions

Please indicate the extent to which you disagree or agree with the following statements regarding $\{e://Field/Condition\}$:

(-3 Strongly disagree to +3 Strongly agree)

- This mitigation measure makes me angry
- This mitigation measure makes me worry
- This mitigation measure makes me proud
- This mitigation measure makes me hopeful
- This mitigation measure makes me fearful

Perceived uncertainty

How certain or uncertain do you think the following statements are regarding $\{e://Field/Condition\}$:

(-3 Very certain to +3 Very uncertain)

- Sufficient natural resources will be available for this measure by 2050 to contribute to climate change mitigation
- The technology for this mitigation measure will be ready by 2050 to contribute to climate change mitigation.
- The costs of implementing and maintaining this mitigation measure will be well established by 2050, so that it can contribute to climate change mitigation.
- There will be sufficient public acceptance and support for this measure by 2050 to help mitigate climate change
- This measure will reach its maximum global potential by 2050 to contribute to climate change mitigation.

Objective knowledge

Please indicate whether you think the following statements are 'true', 'false', or if you do not

know.

Afforestation/reforestation

- Afforestation and reforestation could remove between 1 to 12 gigatons of CO₂eq emissions per year
- A long-term storage of carbon with afforestation and reforestation is certain
- Afforestation and reforestation face uncertainties related to future land availability, water resources, and food demand
- Afforestation and reforestation large-scale projects have caused social conflicts over land
- The costs of afforestation and reforestation are the same in all regions

Green hydrogen

- Green hydrogen could avoid between 1 to 6 gigatons of CO₂eq emissions per year
- The production of green hydrogen has already been tested at large scale
- Green hydrogen faces uncertainties related to access to renewable energy sources
- The costs for green hydrogen will depend on technological innovation, technology growth, and the costs of producing hydrogen with fossil fuels
- Public awareness of green hydrogen is high

BECCS

- BECCS could reduce between 0.5 to 11 gigatons of CO₂eq emissions per year
- BECCS has already been tested at large scale
- BECCS face uncertainties related to future land availability, water resources, and food demand
- The costs for BECCS will depend on technological innovation and technology growth
- Public awareness of BECCS is high

Sustainable diets:

- Shifting towards sustainable diets could avoid between 2 to 5.5 gigatons of CO₂eq emissions per year
- Technologies which make plant-based food more appealing have already been implemented at large scale
- Shifting towards sustainable diets face uncertainties related to future land availability, water resources, and farming conditions
- It is uncertain whether different cultures will accept and adopt plant-based diets
- The costs of shifting to sustainable diets are not influenced by climate conditions

Introduction Part 2

Uncertainty related to the global mitigation potential

Please read this text carefully

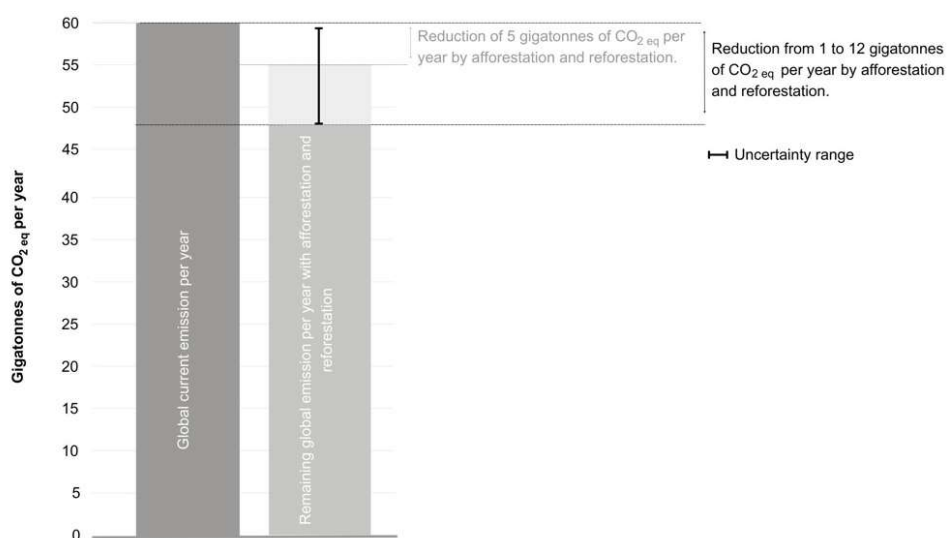
The amount of greenhouse gas emissions that $\{e://Field/Condition\}$ can reduce each year is somewhat uncertain. The main causes of this uncertainty are a lack of knowledge about how much natural resources will be available, how the technology will develop over time, what future costs might look like, and to what extent the public in different countries will accept $\{e://Field/Condition\}$. In the following section of the survey, we will present information about uncertainties related to the global mitigation potential of this measure. Please read the information carefully and answer the subsequent questions. Go to the next page to start part 2 of the study.

Uncertainty information

Uncertainty related to the global mitigation potential of afforestation and reforestation

Please read this text carefully

While the best available estimate indicates that afforestation and reforestation can avoid the emission of 5 gigatons of greenhouse gases (CO₂eq) per year, the range around this estimate extends from 1 to 12 gigatons of CO₂eq per year between 2020 and 2050, as shown in the following graph.



The uncertainty around the mitigation potential of afforestation and reforestation – whether

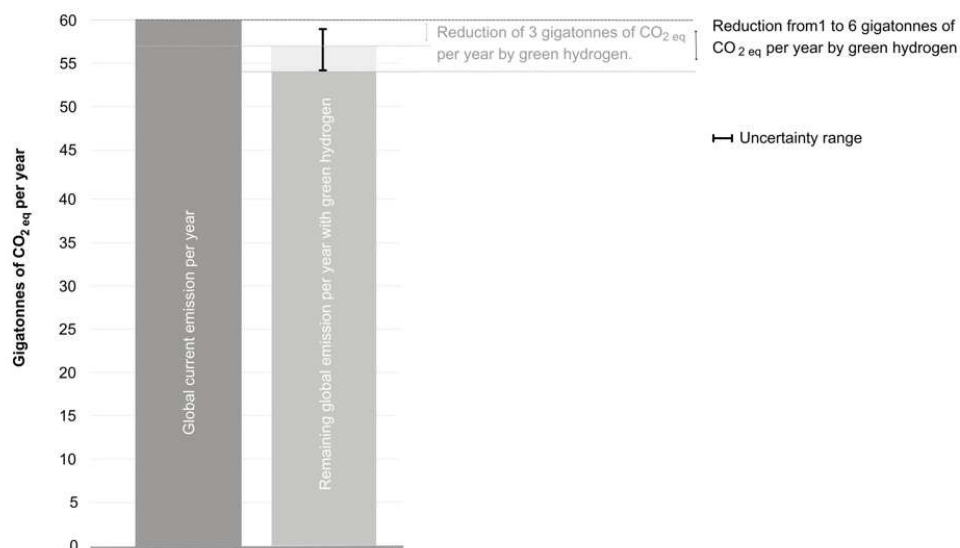
it will reduce 1 gigaton of CO₂eq emissions per year or achieve reductions up to 12 gigatons – depends on several factors:

- Uncertainty remains around the availability of land for afforestation and reforestation, as future farming conditions, land and water availability, food demand, and climate change impacts are unpredictable.
- While the mitigation effect of planting and growing trees are well understood, the long-term storage of carbon in trees is uncertain, and there is no guarantee against deforestation, forest fires, or climate impacts, which could worsen climate change.
- Costs of afforestation and reforestation will vary by region, and it will depend on labor costs.
- Although there is general acceptance of afforestation and reforestation, large-scale projects have also caused social conflicts over land, water, and other environmental impacts, such as planting trees in areas where they did not naturally exist.

Uncertainty related to the global mitigation potential of green hydrogen

Please read this text carefully

While the best available estimate indicates that green hydrogen can avoid the emission of 3 gigatons of greenhouse gases (CO₂eq) per year, the range around this estimate extends from 1 to 6 gigatons of CO₂eq per year between 2020 and 2050, as shown in the following graph.



The uncertainty around the mitigation potential of green hydrogen – whether it will reduce 1 gigatons of CO₂eq emissions per year or achieve reductions up to 6 gigatons – depends on

several factors:

- Producing green hydrogen at large-scale depends on access to renewable energy sources (such as solar or wind power), which may be limited by geography (e.g. sunnier countries will have more solar power).
- Green hydrogen technology has not been tested at a large-scale, and because it depends on complex setups like transportation networks and storage systems, it is not known how effectively it can be built and improved.
- The costs of implementing green hydrogen at a large scale (including the energy needed for hydrogen production and the infrastructure for hydrogen transport and storage) are difficult to estimate and it will depend on the pace of technological innovation, technology growth, and the cost of its competitor: hydrogen produced with fossil fuel (natural gas).
- The extent to which green hydrogen can be implemented depends on public support.
- Currently, it is unclear to what extent the public would accept large-scale production and storage of green hydrogen, as awareness is low, and acceptance will depend on factors such as costs and infrastructure availability, which remain uncertain.

Uncertainty related to the global mitigation potential of bioenergy with carbon capture and storage (BECCS)

Please read this text carefully

While the best available estimate indicates that BECCS can avoid the emission of 6 gigatons of greenhouse gases (CO₂eq) per year globally, the range around this estimate extends from 0.5 to 11 gigatons of CO₂eq per year between 2020 and 2050, as shown in the following graph.



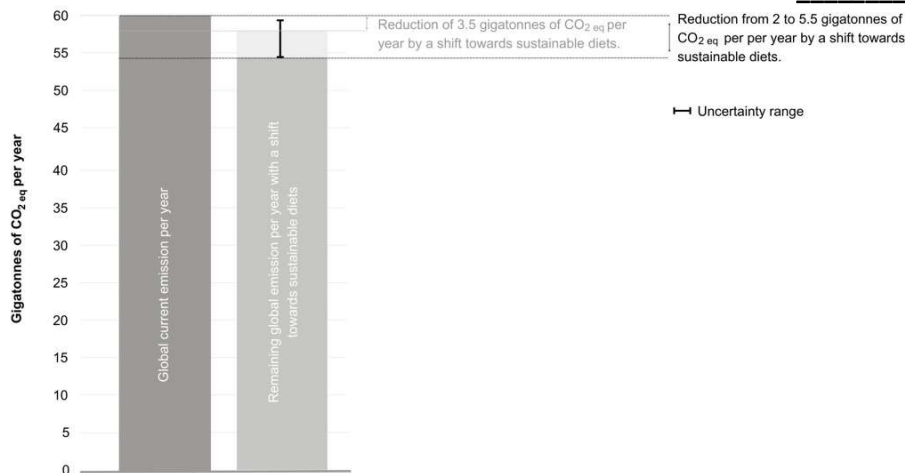
The uncertainty around the mitigation potential of BECCS – whether it will only reduce 0.5 gigatons of CO₂eq emissions per year or achieve reductions up to 11 gigatons – depends on several factors:

- It is unclear how much land can be used for growing plants for BECCS because future farming conditions, land and water availability, food demand, and climate change impacts are hard to estimate.
- BECCS technology has not been tested at a large scale, and because it depends on complex technological setups like large plants, transportation networks, and underground storage systems, it is not known how effectively it can be built and improved.
- The costs of implementing BECCS at a large scale (including growing plants, transporting and storing carbon) are not well understood. They will depend on technological innovation, technology's growth, and vary across global regions.
- The amount at which BECCS can be implemented depends on public support.
- Currently, it is unclear to what extent the public would accept underground carbon storage for BECCS, as awareness of the technology is low and research on public acceptance is limited. Additionally, there is often resistance to growing plants specifically for energy production, as it has led to conflicts over land and water use, as well as environmental impacts such as land degradation and loss of biodiversity.

Uncertainty related to the global mitigation potential of shifting towards sustainable diets

Please read this text carefully

While the best available estimate indicates that a shift towards sustainable diets can avoid the emission of 3.5 gigatons of greenhouse gases (CO₂eq) per year, the range around this estimate extends from 2 to 5.5 gigatons of CO₂eq per year between 2020 and 2050, as shown in the following graph.



The uncertainty around the mitigation potential of shifting towards sustainable diets – whether it will reduce 2 gigaton of CO₂eq emissions per year or achieve reductions up to 5.5 gigatons – depends on several factors:

- Sufficient plant proteins are currently produced worldwide to feed the global population and support a shift toward plant-based diets. However, uncertainties remain regarding future farming conditions, including land and water availability, biodiversity, soil nutrient cycles, and the impacts of climate change on agriculture
- Some emerging technologies, which have not yet been tested at a large-scale but could make plant-based alternatives more appealing to consumers could increase the demand of plant-based diets.
- The price of key ingredients used in plant-based diets, such as soy, peas, and nuts, depends on climate conditions, labor costs, international trade policies, and demand, all of which are difficult to predict.
- While people have the ability to change their diets, it is unclear how different cultures will accept and adopt plant-based diets.

Support mitigation potential level

To implement a mitigation measure, governments must establish the amount of greenhouse gas emissions (CO₂eq) they aim to reduce annually with this measure.

Considering that, according to the best estimate, bioenergy with carbon capture and storage **{e://Field/Condition}** can avoid [X] gigatons of greenhouse gas emissions (CO₂eq) per year, we would like to know your level of support for this measure if it were to be used to reduce

different amounts of emissions.

To what extent would you support policies which promote the construction of \${e://Field/Condition} in [COUNTRY], to achieve the following levels of CO₂eq emission reductions per year? Keep in mind that the amount of CO₂eq emissions reduced is proportional to the scale at which \${e://Field/Condition} would need to be implemented.

Instructions: Use the arrow on the right side of the box to move to the next level of CO₂eq emissions reduction per year. If you want to return to the previous level, use the arrow on the left side of the box.

(-2 Strongly oppose to +2 Strongly support)

Afforestation/reforestation

- 4.5 gigatons of CO₂eq or more
- only between 2.5 and 4.5 gigatons of CO₂eq
- and if it was only between 1 and 2.5 gigatons of CO₂eq, would you support or oppose?
- what about up to only 1 gigaton of CO₂eq, would you still support or oppose?

Green hydrogen

- 2.5 gigatons of CO₂eq or more
- only between 1.75 and 2.5 gigatons of CO₂eq
- and if it was only between 1 and 1.75 gigatons of CO₂eq, would you support or oppose?
- what about up to only 1 gigaton of CO₂eq, would you still support or oppose?

BECCS

- 5 gigatons of CO₂eq or more per year
- only between 2.5 and 5 gigatons of CO₂eq per year
- and if it was only between 1 and 2.5 gigatons of CO₂eq per year, would you support or oppose?
- what about up to only 1 gigaton of CO₂eq per year, would you still support or oppose?

Sustainable diets

- 3 gigatons of CO₂eq or more
- only between 2 and 3 gigatons of CO₂eq
- and if it was only between 1 and 2 gigatons of CO₂eq, would you support or oppose?
- what about up to only 1 gigaton of CO₂eq, would you still support or oppose?

Do you have any additional comments about this study that you would like to share with us?

A3. Sample characteristics

Table 1. Sample characteristics: Descriptives of socio-demographic factors, political trust, trust in climate scientists, climate change beliefs, and subjective knowledge.

Characteristics	Germany N=558	Spain N=566	France N=571	Italy N=573	Netherlands N=521	Poland N=562
<i>Gender (%)</i>						
Female	51	52	52	51	53	53
Male	49	48	48	49	47	47
Other	0	0	0	1	0	1
<i>Age (%)</i>						
18-29	14	18	19	16	18	19
30-39	19	17	16	16	19	21
40-49	16	22	17	19	17	20
50-59	20	20	18	22	19	18
60+	31	22	30	27	28	22
<i>Education Level (%)</i>						
Primary education	22	24	10	18	2	4
Secondary education	47	32	47	53	49	61
Tertiary education	30	43	43	29	49	35
<i>Income (%)</i>						
Low income	37	29	22	39	21	19
Medium income	28	41	40	39	33	35
Medium-high income	18	19	22	9	31	38

High income	11	7	12	7	8	4
<i>Individual characteristics (mean)</i> (Likert scale from -3 (strongly disagree) to +3 (strongly agree))						
Political trust	-0.62	-0.44	-0.61	-0.71	-0.75	-0.48
Trust in climate scientists	0.54	0.48	0.32	0.69	0.41	0.06
Climate change belief	1.22	1.71	1.57	1.63	1.12	1.12
<i>Subjective Knowledge (mean)</i> (Likert scale from 1 (no knowledge) to 5 (very good knowledge))						
Self-assessed knowledge	2.35	2.35	2.18	2.32	2.36	2.47

A.4 Statistical analysis

To assess changes in *objective knowledge*, *acceptance/support*, and *affect* across time and mitigation measures, we conducted a series of repeated measures analyses of variance (ANOVAs) using the `aov_car()` function from the *afex* package in R. We specified Type III sum of squares to account for unequal group sizes. First, we analyzed the change in *objective knowledge* using a repeated measures ANOVA, including *Condition* (mitigation measures) and *Time* (initial vs. informed), and their interaction as predictors. To test whether the magnitude of *objective knowledge* gain differed significantly between measures, we conducted a one-way ANOVA (Type I sum of squares) on the calculated difference scores (post-pre), with Tukey's post-hoc comparisons. Next, to examine the effect of information on *acceptance/support* and *affect*, as well as differences across mitigation measures and countries, we used a repeated measures ANOVA, including *Condition*, *Time*, and *Countries*, and all their interactions as predictors. All post-hoc pairwise comparisons were conducted on the estimated marginal means (*emmeans* package) with a Bonferroni correction to adjust the *p*-values¹. We calculated Cohen's *d* for paired samples to quantify the effect size of the initial to informed change on *acceptance/support* and *affect*. To determine if the magnitude of this change differed significantly across mitigation measures, we again used a one-way ANOVA on the difference scores, followed by a Tukey's post-hoc test.

To analyze the influence of *perceived uncertainty* on participants' *acceptance/support* and *affect*, we conducted a multi-stage analysis using repeated measures ANOVA and multilevel models (*lme4* package) in R. First, to find whether uncertainty information altered levels of *perceived uncertainty*, we conducted a series of repeated measures ANOVAs for each of the five perceived uncertainty dimensions. Each ANOVA included *Condition*, *Time*, and their

interaction. We then performed a one-way ANOVA on the change in a composite *perceived uncertainty* score (computed as the average of the five measured uncertainty dimensions) to test if the magnitude of this change differed significantly across mitigation measures. Next, to better understand the influence of *perceived uncertainty*, we decomposed each *perceived uncertainty* variable into two components: a stable between-person effect (reflecting each participant's average perceived uncertainty across time) and a dynamic within-person effect (the time-varying deviation from that person's average) ²⁻⁴ (see Supplementary Material A.8). We then modeled *acceptance/support* and *affect* as a function of all ten decomposed uncertainty components simultaneously. This model was specified for both the overall dataset (controlling for *Condition*) and separately for each of the four mitigation measures. Finally, to test how the delivery of uncertainty information changes the influence of *perceived uncertainty* on *acceptance/support* and *affect*, we modeled the interaction between *Time* and the raw, undecomposed *perceived uncertainty* scores. This multilevel model was applied to both the general data (controlling for *Condition*) and to each of the four mitigation measures individually. For all multilevel models, we report marginal (R^2_{marginal}) and conditional ($R^2_{\text{conditional}}$) R^2 values calculated via the Nakagawa method ⁵ to assess model fit for fixed and random effects.

Finally, to identify the most influential individual-level drivers of *acceptance/support* and *affect*, we specified a set of final multilevel models, one for each predictive variable. These models were designed to assess the unique predictive power of beliefs, trust, and socio-demographic factors after accounting for the influence of perceived uncertainty. The models included four sets of fixed effects: (1) beliefs, trust, and knowledge (*climate change belief*, *trust in climate scientists*, *political trust*, and *subjective knowledge*); (2) socio-demographic factors (*age*, *gender*, *income*, and *education level*); (3) all ten decomposed between- and within-person *perceived uncertainty* components; and (4) a control variable for *Condition*. By including all predictors simultaneously, we could isolate the unique influence of each socio-demographic, belief, trust, and subjective knowledge variable, independent from the effects of perceived uncertainty. The model included a random intercept for each participant, and we report marginal and conditional R^2 values to assess overall model fit

A.5 Objective knowledge



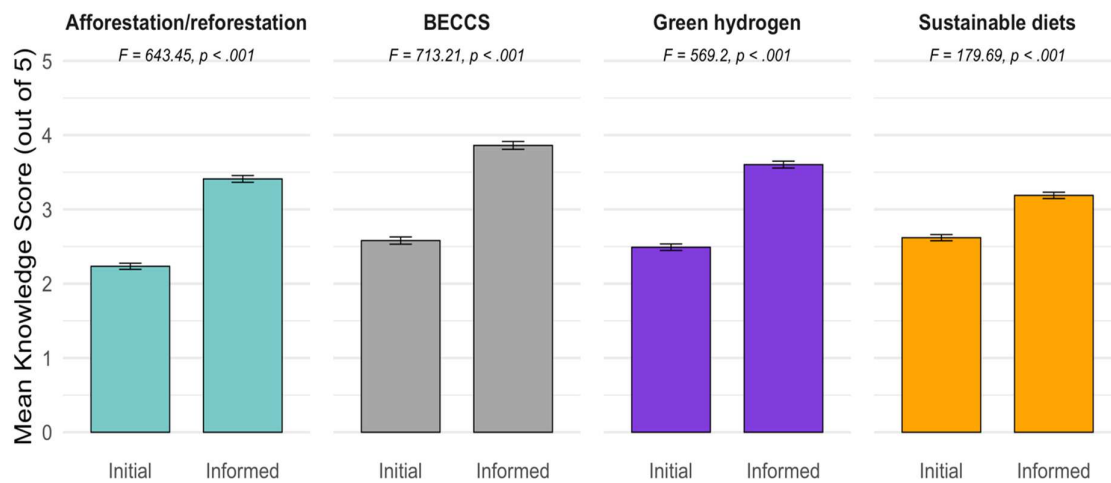


Figure 6 Change in objective knowledge by mitigation measure. The figure shows the mean objective knowledge score (out of 5) for each mitigation measure, both before (Initial) and after (Informed) the provision of information. Points represent the mean scores, and error bars depict the standard error. The F-statistic and p-value within each panel are from a repeated measures ANOVA testing the significant difference between knowledge scores pre vs. post information.

A.6 Initial and Informed affect across mitigation measures, and country

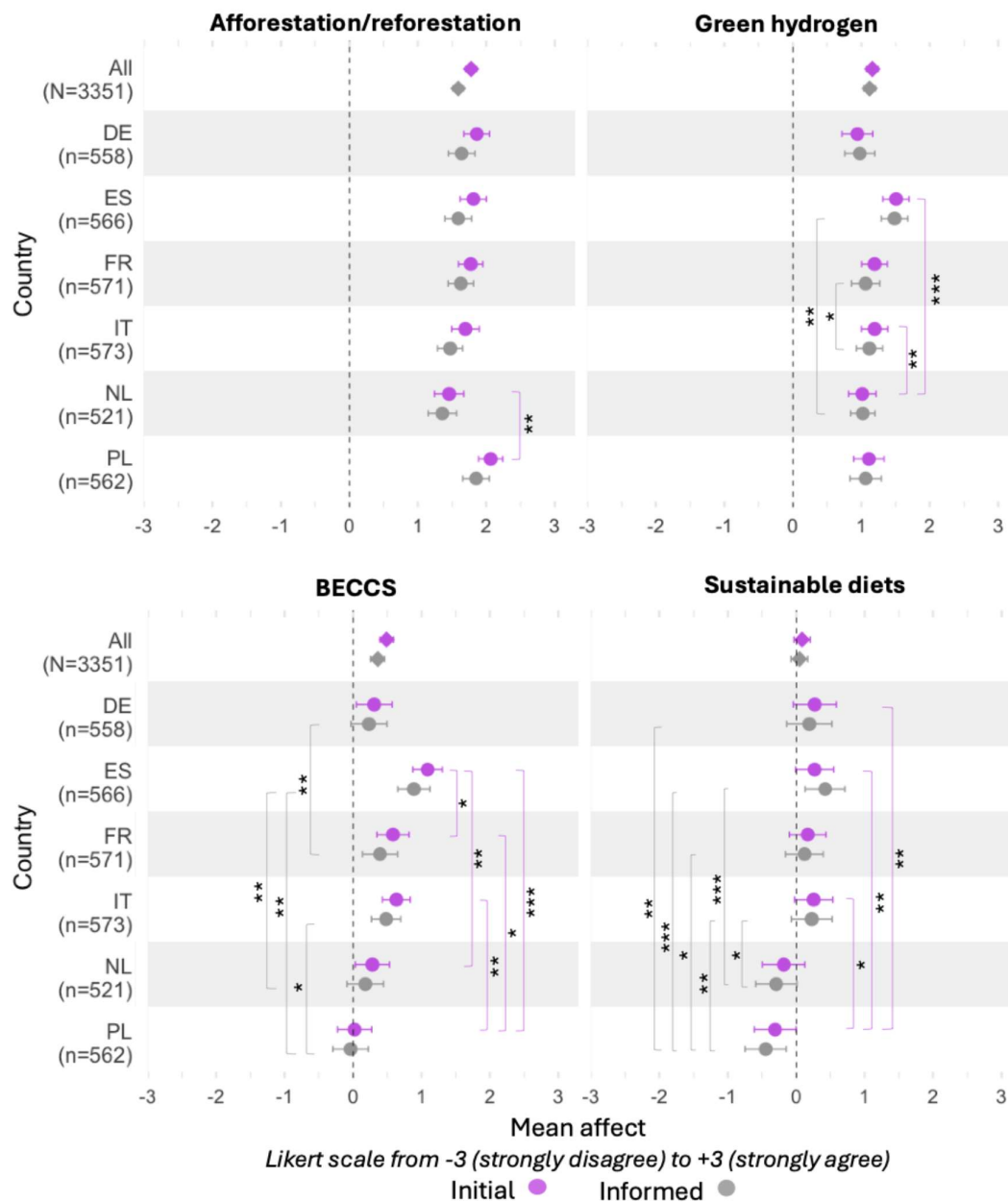
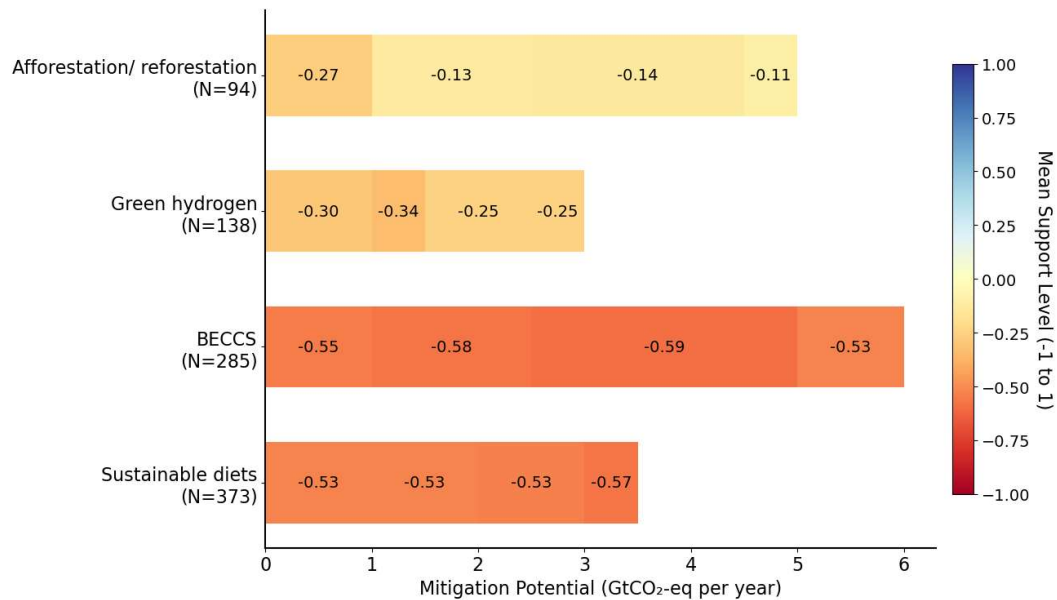


Figure 7. Initial and informed mean affect for each mitigation measure across countries. Points represent means with standard errors. Statistical differences between countries' initial (purple) and informed (gray) values are indicated by connecting lines and asterisks ($F: 3.37, p < .001$). Overall means between mitigation measures were all statistically significant ($F: 242, p < .001$). Significant differences were assessed using repeated measures ANOVA followed by Bonferroni-adjusted post hoc comparisons. Significance levels: * $p < .05$, ** $p < .01$, *** $p < .001$

A.7 Support for mitigation potential levels

A.



B.

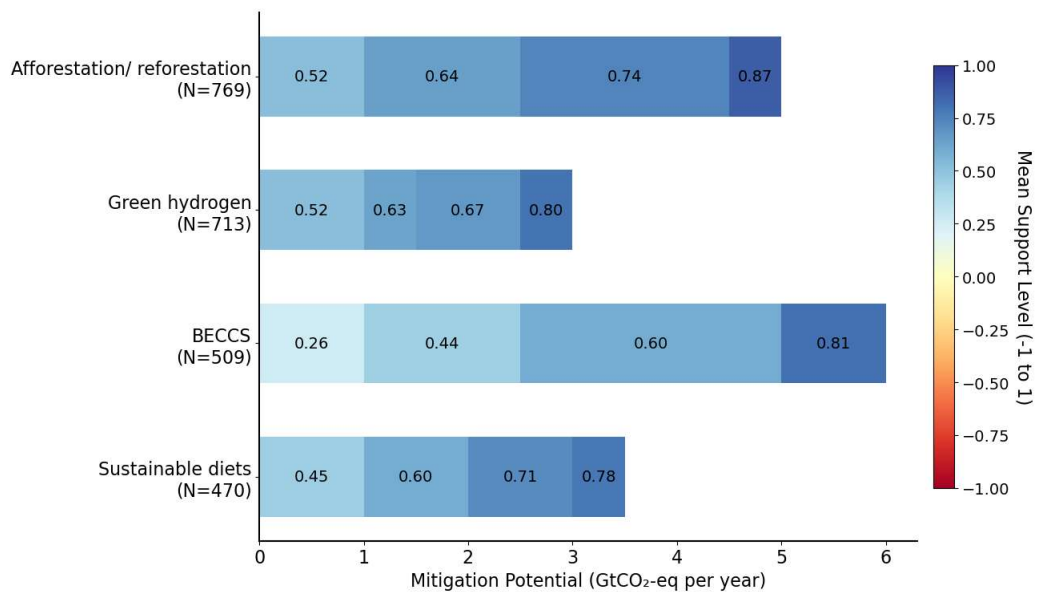


Figure 8. Mean support of Opposers/Undecided (A) and Supporters (B), for different levels of mitigation potential. Numbers within the bars indicate the mean level of public support for each mitigation measure at a given mitigation potential level. The color gradient represents supportive or opposing levels: blue shades indicate positive support, red shades indicate opposition, and darker colors reflect stronger opinions.

A.8 Initial and informed perceived uncertainty across dimensions and mitigation measures

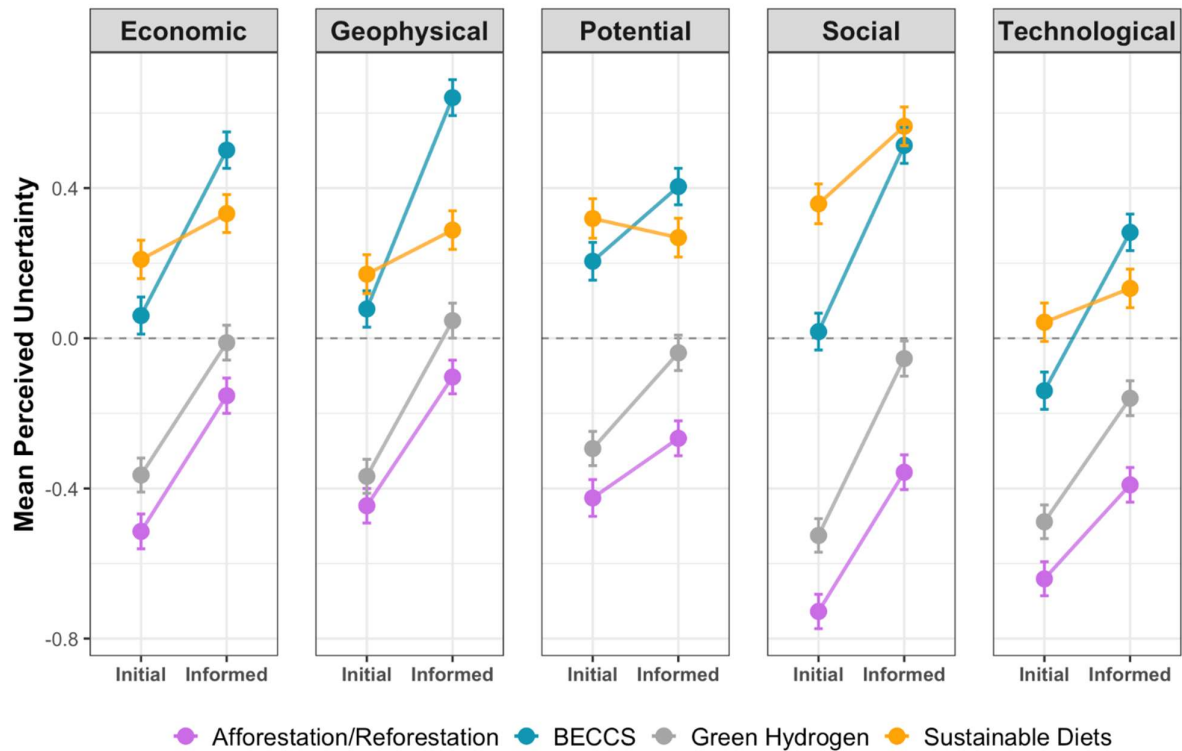


Figure 9 Change in perceived uncertainty before (Initial) and after (Informed) the provision of information across mitigation measures and feasibility uncertainties. Colored points represent means and standard errors of perceived uncertainty for each mitigation measure per feasibility uncertainty. Colored lines represent the change in mean perceived uncertainty from Initial to Informed values.

A.9 Initial and informed mean emotional responses across mitigation measures

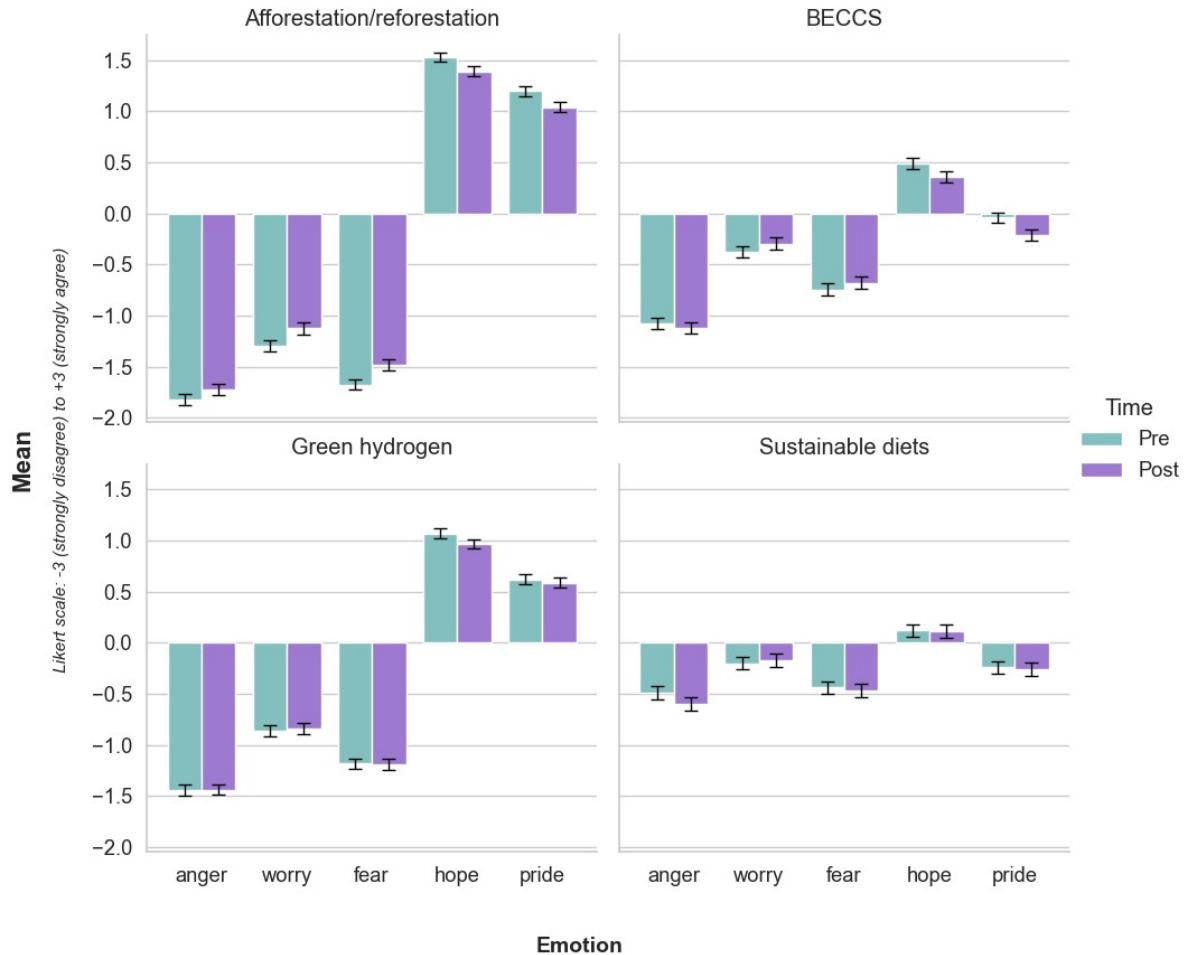


Figure 10 Initial and informed mean emotional responses to climate mitigation measures. The chart displays mean ratings for five emotions (anger, worry, fear, hope, pride) measured before (Pre) and after (Post) the provision of information. Responses are on a 7-point Likert scale from -3 (strongly disagree) to +3 (strongly agree). Error bars represent the standard error of the mean

A.10. Effect of perceived uncertainty: multilevel model between and within effects

We decomposed each perceived feasibility uncertainty into a between-person component (individual mean across pre- and post-information timepoints) and a within-person component (deviation from the individual mean at each timepoint). These components were entered as separate predictors in a multilevel model predicting *acceptance/support* and *affect*. The model included random intercepts for participants and fixed effects for mitigation measure (Condition).

1. Decomposition of Perceived Uncertainty

$$PU_{it} = PU_i^- + (PU_{it} - PU_i^-)$$

- PU_{it} represents the perceived uncertainty score for participant i at time t .
- $PU_i^- = \frac{1}{2}(PU_{i,pre} + PU_{i,post})$ represents the person-mean perceived uncertainty (between-person effect)
- $PU_{it} - PU_i^-$ represents the within-person deviation from the individual average (within-person effect)

2. Multilevel Model Specification

$$Y_{it} = \beta_0 + \beta_1 \cdot PU_{within, it} + \beta_2 \cdot PU_{between, i} + \gamma \cdot Condition_i + u_i + \epsilon_{it}$$

- Y_{it} is the dependent variable (acceptance/support or affect)
- β_0 is the value of Y_{it} when all predictors = 0
- β_1 is the effect of changes in uncertainty within individuals (within-person). It captures the within-person deviation- how the acceptance of the individual changes when their perceived uncertainty deviates from their own average.

- β_2 is the effect of individuals' overall level of perceived uncertainty (between-person). It captures the between-person effect- whether a person who constantly perceive higher uncertainty regardless of information will have a higher or lower acceptance compared to a person who generally perceived lower uncertainty.
- $\gamma * Condition$ represents the fixed effect for each *Condition* (mitigation measure) relative to a reference category (e.g. afforestation/reforestation)
- u_i participant-level random intercept
- ε_{it} is the residual error

Table 2 Between- and within-person effects of perceived uncertainty on acceptance/support and affect across mitigation measures

(A)

Condition	Acceptance/Support									
	Geophysical		Technological		Economic		Social		Potential	
	β	CI	β	CI	β	CI	β	CI	β	CI
<i>Between-person</i>										
BECCS	-0.24***	[-0.36, -0.11]	-0.36***	[-0.48, -0.24]	-0.08	[-0.21, 0.05]	-0.16*	[-0.28, -0.04]	-0.1	[-0.23, 0.03]
Green hydrogen	-0.11.	[-0.22, 0]	-0.24***	[-0.36, -0.12]	-0.06	[-0.18, 0.06]	-0.23***	[-0.34, -0.12]	0	[-0.12, 0.11]
Afforestation/reforestation	0.12*	[0.01, 0.23]	-0.27***	[-0.37, -0.16]	0.01	[-0.1, 0.12]	-0.27***	[-0.36, -0.17]	-0.06	[-0.18, 0.05]
Sustainable diets	-0.01	[-0.18, 0.17]	-0.39***	[-0.56, -0.21]	-0.21*	[-0.39, -0.03]	-0.27**	[-0.43, -0.11]	-0.2*	[-0.39, -0.02]
<i>Within-person</i>										

BECCS	-0.03*	[-0.06, 0]	-0.01	[-0.04, 0.02]	0.01	[-0.02, 0.04]	-0.05***	[-0.08, -0.02]	0	[-0.03, 0.03]
Green										
hydrogen	-0.02.	[-0.04, 0]	-0.02.	[-0.04, 0]	-0.01	[-0.03, 0.02]	-0.04***	[-0.07, -0.02]	-0.01	[-0.03, 0.02]
Afforestation/ reforestation	-0.01	[-0.04, 0.01]	0.01	[-0.01, 0.04]	-0.03*	[-0.05, 0]	-0.05***	[-0.08, -0.03]	0	[-0.02, 0.03]
Sustainable diets	-0.01	[-0.03, 0.02]	0.01	[-0.01, 0.04]	-0.03**	[-0.06, -0.01]	0	[-0.03, 0.02]	0.01	[-0.01, 0.04]

(B)

Condition	Affect									
	Geophysical		Technological		Economic		Social		Potential	
	β	CI	β	CI	β	CI	β	CI	β	CI
<i>Between-person</i>										
BECCS	-0.33***	[-0.46, -0.21]	-0.22***	[-0.34, -0.09]	-0.21**	[-0.34, -0.08]	-0.19**	[-0.31, -0.07]	-0.08	[-0.2, 0.05]
Green										
hydrogen	-0.04	[-0.16, 0.08]	-0.28***	[-0.41, -0.16]	-0.15*	[-0.28, -0.02]	-0.28***	[-0.4, -0.16]	0	[-0.13, 0.12]
Afforestation/ reforestation	0.13*	[0.01, 0.26]	-0.24***	[-0.35, -0.12]	-0.03	[-0.15, 0.09]	-0.26***	[-0.36, -0.15]	-0.09	[-0.21, 0.03]
Sustainable diets	-0.06	[-0.25, 0.12]	-0.44***	[-0.63, -0.25]	-0.18.	[-0.37, 0.01]	-0.32***	[-0.49, -0.14]	-0.19*	[-0.39, 0]
<i>Within-person</i>										
BECCS	-0.14**	[-0.24, -0.04]	-0.18***	[-0.28, -0.08]	-0.15**	[-0.25, -0.06]	-0.06	[-0.15, 0.04]	-0.03	[-0.12, 0.05]
Green										
hydrogen	-0.17***	[-0.25, -0.08]	-0.11**	[-0.2, -0.03]	-0.04	[-0.12, 0.05]	-0.09*	[-0.18, -0.01]	0.02	[-0.06, 0.1]



Afforestation/ reforestation	-0.03	[-0.12, 0.06]	-0.07	[-0.16, 0.01]	-0.09.	[-0.17, 0]	-0.18***	[-0.27, -0.1]	0.02	[-0.07, 0.1]
Sustainable diets	-0.1*	[-0.21, 0]	-0.04	[-0.15, 0.06]	-0.16**	[-0.26, -0.05]	-0.04	[-0.14, 0.06]	-0.2***	[-0.3, -0.09]
<i>Time: within-person</i>										
BECCS	0.13	[-0.05, 0.32]	0.33***	[0.15, 0.52]	0.3**	[0.12, 0.47]	0.05	[-0.12, 0.21]	0.13	[-0.05, 0.3]
Green hydrogen	0.28***	[0.13, 0.44]	0.18*	[0.03, 0.34]	0.03	[-0.13, 0.18]	-0.07	[-0.22, 0.09]	0.17*	[0.01, 0.33]
Afforestation/ reforestation	0.05	[-0.12, 0.21]	0.1	[-0.06, 0.26]	0.09	[-0.07, 0.26]	-0.01	[-0.17, 0.14]	0.28***	[0.12, 0.44]
Sustainable diets	0.22*	[0.02, 0.42]	0.18.	[-0.03, 0.38]	0.16	[-0.04, 0.36]	0.29**	[0.09, 0.49]	0.04	[-0.16, 0.24]

*Note. This table shows the unstandardized coefficients (β), standard errors (SE), and 95% confidence intervals [CI] from four separate multilevel models, one for each mitigation measure. Each model predicts acceptance/support (A) or affect (B) as a function of the between-person and within-person components of all five uncertainty dimensions. Marginal R^2 values for these models were as follow: Acceptance/support: 0.39 (BECCS), 0.17 (Afforestation/reforestation), 0.29 (Green hydrogen), 0.37 (Sustainable diets) ; Affect: 0.41 (BECCS), 0.15 (Afforestation/reforestation), 0.30 (Green hydrogen), 0.38 (Sustainable diets) Significance levels: * $p < .05$, ** $p < .01$, *** $p < .001$.*

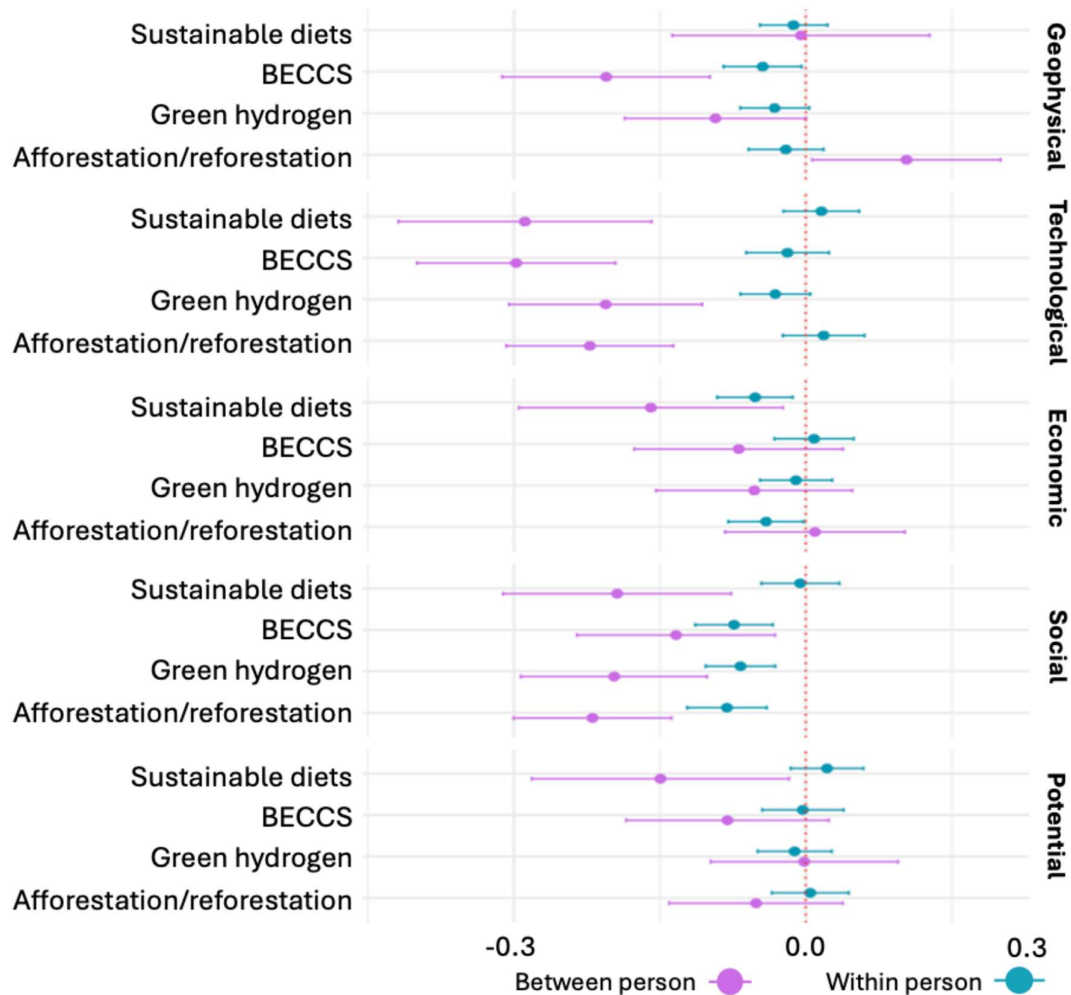


Figure 7 Between- and within-person effects of perceived uncertainty on acceptance/support across mitigation measures. This figure shows the unstandardized regression coefficients (β) and 95% confidence intervals from four separate multilevel models, one for each mitigation measure. Each model predicts acceptance/support as a function of the between-person (purple) and within-person (blue) components of all five uncertainty dimensions. An effect is statistically significant ($p < .05$) if its confidence interval does not cross the zero line. Marginal R^2 values for these models were as follows: 0.39 (BECCS), 0.17 (Afforestation/reforestation), 0.29 (Green hydrogen), 0.37 (Sustainable diets)

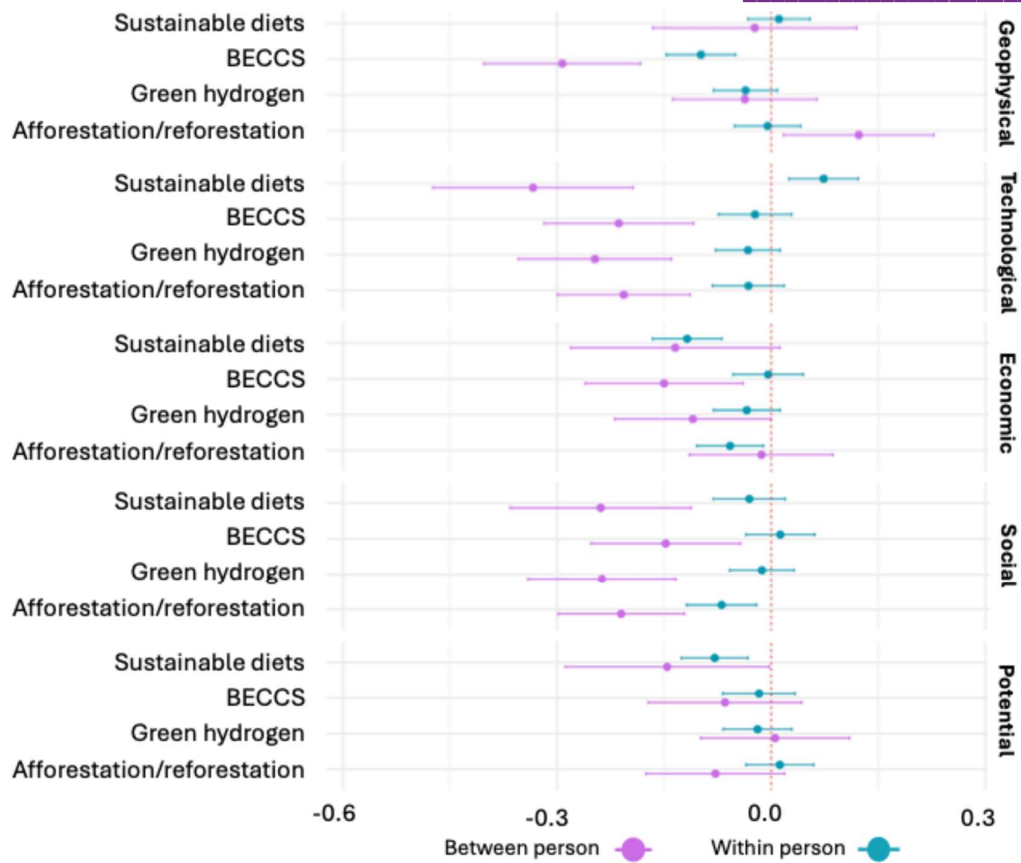


Figure 8 Between- and within-person effects of perceived uncertainty on affect across mitigation measures. This figure shows the unstandardized regression coefficients (β) and 95% confidence intervals from four separate multilevel models, one for each mitigation measure. Each model predicts affect as a function of the between-person (purple) and within-person (blue) components of all five uncertainty dimensions. An effect is statistically significant ($p < .05$) if its confidence interval does not cross the zero line (red dashed line). Marginal R^2 values for these models were as follows: 0.41 (BECCS), 0.15 (Afforestation/reforestation), 0.30 (Green hydrogen), 0.38 (Sustainable diets)

A.11 Impact of information on the effect of perceived uncertainty

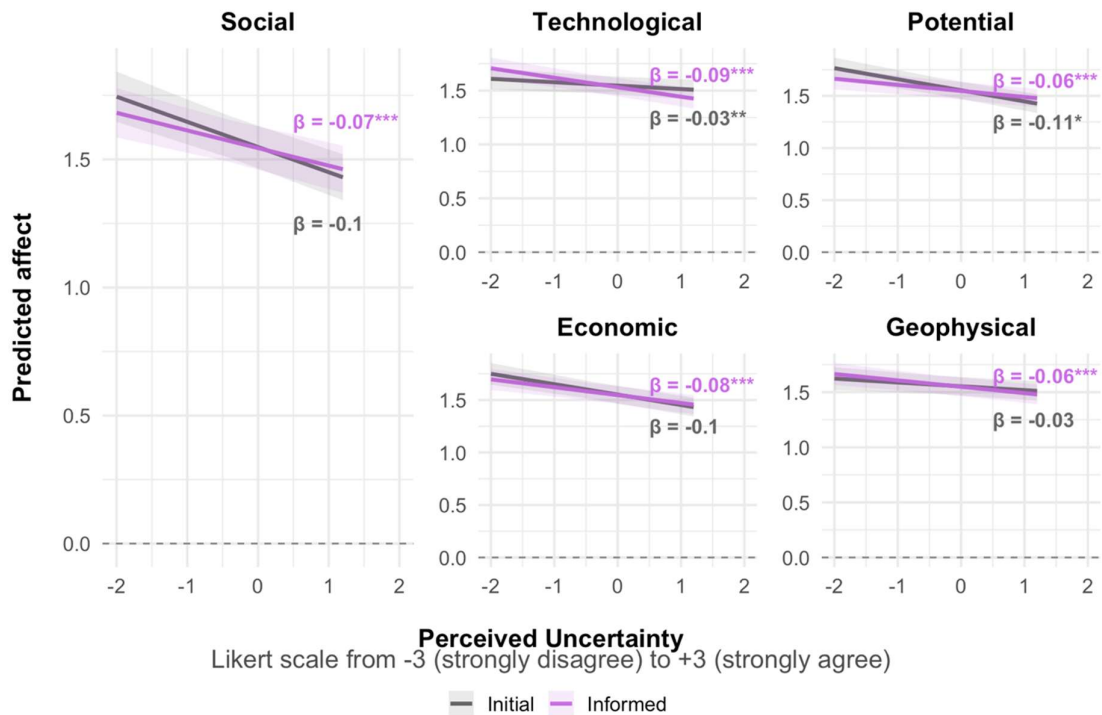


Figure 9 Change in the influence of perceived uncertainty on affect. The figure displays the predicted relationship between perceived social, technological, potential, economic, and geophysical uncertainties and affect, both before (Initial, purple) and after (Informed, gray) information. Slopes are derived from a single multilevel model that includes the interaction between time and each feasibility uncertainty, while controlling for the mitigation measure. Shaded bands represent 95% confidence intervals. The annotated slope value (β) at the end of each line represents the unique predictive power of that uncertainty dimension at that time point. A star (*) next to the "Informed" slope indicates that the change in the slope from Initial to Informed was statistically significant. Significance levels: * $p < .05$, ** $p < .01$, *** $p < .001$.

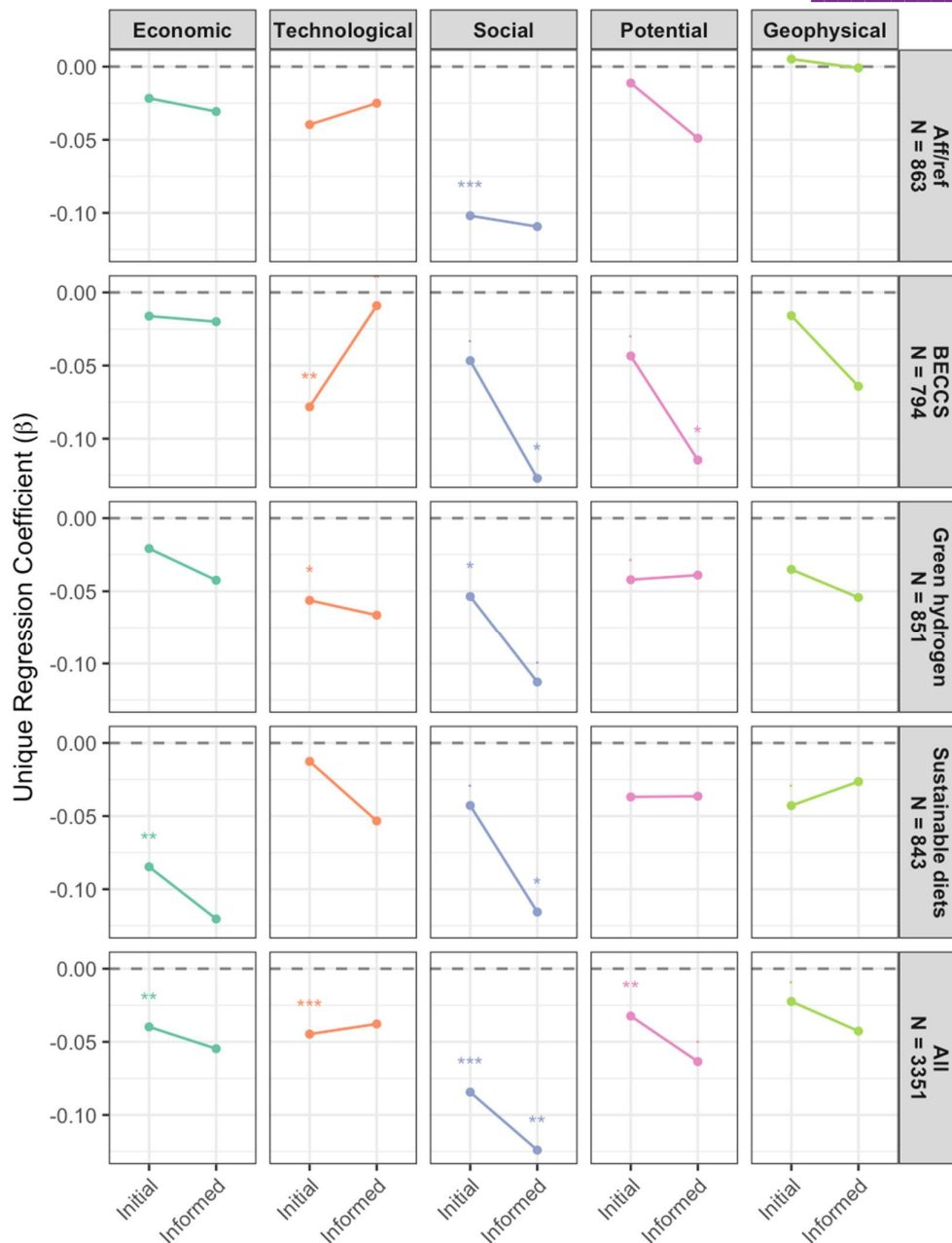


Figure 10 Change in the unique predictive strength of perceived uncertainties on acceptance/support across time and mitigation measures. This figure displays the change in the unique regression coefficients (β) for each of the five perceived uncertainty dimensions, estimated from five separate multilevel models predicting acceptance/support. The last row, "All," shows results from a model using the pooled dataset, while the other rows show results from models run independently for each mitigation measure. Within each model, all five uncertainty dimensions and their interactions with time were included simultaneously. The points represent the unique predictive power of each uncertainty at the "Initial" and "Informed" time points. Stars on "Initial" indicate that this relation was statistically significant before the information. A star on "Informed" indicates that the change in the coefficient ($\beta_{\text{initial}} - \beta_{\text{informed}}$) was itself statistically significant. Significance levels: * $p < .05$, ** $p < .01$, *** $p < .001$.

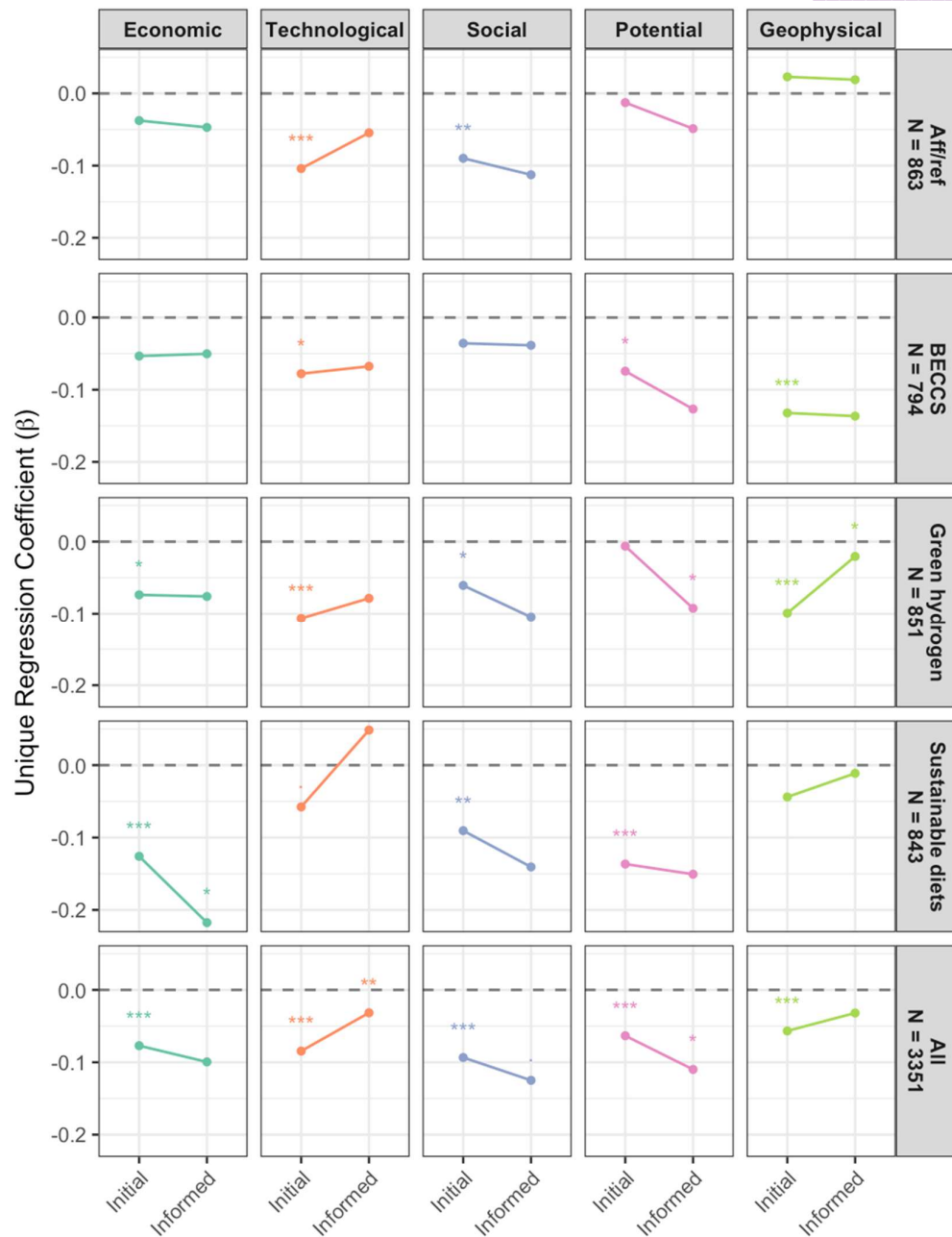


Figure 11 Change in the unique predictive strength of perceived uncertainties on affect across time and mitigation measure. This figure displays the change in the unique regression coefficients (β) for each of the five perceived uncertainty dimensions, estimated from five separate multilevel models predicting affect. The last row, "All", shows results from a model using the pooled dataset, while the other rows show results from models run independently for each mitigation measure. Within each model, all five uncertainty dimensions and their interactions with time were included simultaneously. The points represent the unique predictive power of each uncertainty at the "Initial" and "Informed" time points. Stars on "Initial" indicate that this relation was statistically significant before the information. A star on "Informed" indicates that the change in the coefficient ($\beta_{\text{initial}} - \beta_{\text{informed}}$) was itself statistically significant. Significance levels: * $p < .05$, ** $p < .01$, *** $p < .001$.

A.12 Fixed effect estimates from multilevel mixed models predicting acceptance and affect

Table 3. Multilevel model predicting acceptance/support for climate mitigation measures

Predictor	β	SE	95% CI	p
Intercept	0.55	0.08	[0.40, 0.71]	< .001
<i>Beliefs and Trust</i>				
Political Trust	-0.03	0.01	[-0.06, -0.01]	.004
Climate Change Belief	0.32	0.02	[0.29, 0.36]	< .001
Trust in Scientists	0.18	0.02	[0.15, 0.21]	< .001
<i>Socio-demographics</i>				
Age	0.00	0.00	[0.00, 0.01]	.001
gender	-0.07	0.03	[-0.14, -0.01]	.023
Income	-0.00	0.00	[-0.00, 0.00]	.185
Education	-0.00	0.00	[-0.00, 0.00]	.839
<i>Subjective knowledge</i>				
Assessed Knowledge	0.07	0.02	[0.04, 0.11]	< .001
<i>Conditions (mitigation measures)</i>				
BECCS vs. Aff/ref	-0.63	0.05	[-0.73, -0.53]	< .001
Green Hydrogen vs. Aff/ref	-0.27	0.05	[-0.36, -0.17]	< .001
Sustainable Diets vs. Aff/ref	-1.06	0.05	[-1.15, -0.97]	< .001
<i>Perceived uncertainties (between and within effect)</i>				
Geophysical uncertainty (within)	-0.04	0.01	[-0.07, -0.01]	.003
Geophysical uncertainty (between)	-0.10	0.03	[-0.17, -0.04]	.003
Technological uncertainty (within)	-0.01	0.01	[-0.03, 0.02]	.655

Table 3. Multilevel model predicting acceptance/support for climate mitigation measures

Predictor	β	SE	95% CI	p
Technological uncertainty (between)	-0.25	0.03	[-0.32, -0.18]	< .001
Economic uncertainty (within)	-0.04	0.01	[-0.07, -0.01]	.006
Economic uncertainty (between)	-0.00	0.04	[-0.07, 0.07]	.935
Social uncertainty (within)	-0.09	0.01	[-0.11, -0.06]	< .001
Social uncertainty (between)	-0.25	0.03	[-0.32, -0.19]	< .001
Potential uncertainty (within)	0.00	0.01	[-0.02, 0.03]	.746
Potential uncertainty (between)	-0.09	0.03	[-0.16, -0.03]	.007

Note. This table displays the unstandardized coefficients (β), standard errors (SE), and 95% confidence intervals [CI] from a multilevel model. The model includes decomposed between- and within-person perceived feasibility uncertainty, beliefs, trust, knowledge, and socio-demographic factors as predictors, while controlling for the specific mitigation measure. $N_{obs} = 6702$, $N_{groups} = 3351$.

Marginal $R^2 = 0.53$, Conditional $R^2 = 0.90$.

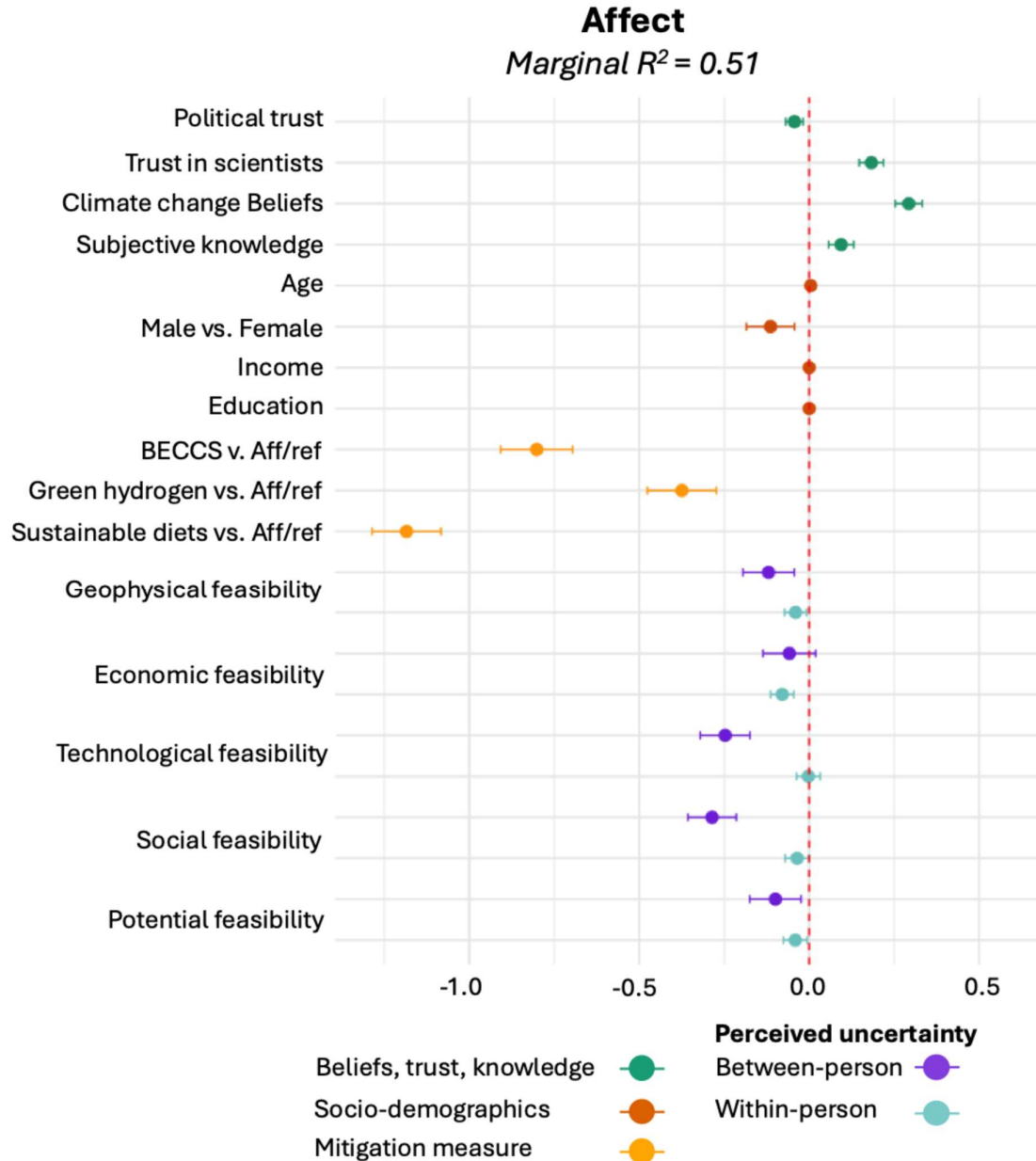


Figure 12 Fixed-effect estimates from multilevel mixed models predicting affect as a function of beliefs, trust, knowledge, sociodemographic characteristics, and perceived uncertainties. Variables include beliefs, trust, and subjective knowledge (green); socio-demographic characteristics (red; gender is relative to female); mitigation measure type (orange; relative to afforestation/reforestation); between-person (purple) and within-person (blue) perceived uncertainty effects. Effects are considered statistically significant at the 95% confidence level if their confidence intervals do not cross zero (red dashed line). Positive values indicate higher affect associated with stronger beliefs, trust, or higher subjective knowledge; negative values indicate lower affect with higher perceived uncertainty or when compared to the reference category. The marginal R^2 value indicates the proportion of variance explained by the predictor variables only.

Table 4. Multilevel Model Predicting Affect for Climate Mitigation Measures

Predictor	β	SE	95% CI	p
Intercept	0.54	0.09	[0.36, 0.71]	< .001
<i>Beliefs and Trust</i>				
Political Trust	-0.04	0.01	[-0.07, -0.02]	< .001
Climate Change Belief	0.29	0.02	[0.25, 0.33]	< .001
Trust in Scientists	0.18	0.02	[0.15, 0.22]	< .001
<i>Socio-demographics</i>				
Age	0.00	0.00	[0.00, 0.01]	< .001
Gender (Female vs. Male)	-0.11	0.04	[-0.18, -0.04]	.002
Income	-0.00	0.00	[-0.00, 0.00]	.586
Education	-0.00	0.00	[-0.00, 0.00]	.925
<i>Subjective knowledge</i>				
Assessed Knowledge	0.09	0.02	[0.06, 0.13]	< .001
<i>Conditions (mitigation measures)</i>				
BECCS vs. Aff/ref	-0.80	0.05	[-0.91, -0.70]	< .001
Green Hydrogen vs. Aff/ref	-0.37	0.05	[-0.48, -0.27]	< .001
Sustainable Diets vs. Aff/ref	-1.18	0.05	[-1.29, -1.08]	< .001
<i>Perceived uncertainties (between and within effect)</i>				
Geophysical uncertainty (within)	-0.04	0.02	[-0.07, -0.01]	.015
Geophysical uncertainty (between)	-0.12	0.04	[-0.20, -0.04]	.002
Technological uncertainty (within)	-0.00	0.02	[-0.04, 0.03]	.890
Technological uncertainty (between)	-0.25	0.04	[-0.32, -0.17]	< .001
Economic uncertainty (within)	-0.08	0.02	[-0.11, -0.05]	< .001
Economic uncertainty (between)	-0.06	0.04	[-0.14, 0.02]	.140
Social uncertainty (within)	-0.04	0.02	[-0.07, -0.00]	.047

Table 4. Multilevel Model Predicting Affect for Climate Mitigation Measures

Predictor	β	SE	95% CI	p
Social uncertainty (between)	-0.29	0.04	[-0.36, -0.21]	< .001
Potential uncertainty (within)	-0.04	0.02	[-0.08, -0.01]	.022
Potential uncertainty (between)	-0.10	0.04	[-0.17, -0.02]	.010

Note. This table displays the unstandardized coefficients (β), standard errors (SE), and 95% confidence intervals [CI] from a linear mixed-effects model. The model includes decomposed between- and within-person perceived feasibility uncertainty, beliefs, trust, knowledge, and socio-demographic factors as predictors, while controlling for the specific mitigation measure. Perceived uncertainty, $N_{\text{obs}} = 6702$, $N_{\text{groups}} = 3351$.

Marginal $R^2 = 0.51$, Conditional $R^2 = 0.87$.

A.13. Initial and informed evaluations and the effect of perceived uncertainty, across mitigation measures

Mitigation Measure	Public Standing (Initial and Informed)	Perceived Uncertainty (Initial and Informed)	Key Uncertainty Drivers (Between-Person Effect) of acceptance/support and affect	Impact of Information on Perceived Uncertainty's Predictive Strength
Afforestation/ reforestation	High: Started as the most popular measure and remained the highest-ranked, despite a significant drop in acceptance/support and affect after information.	Low-to-Moderate: Started with the lowest perceived uncertainty across all dimensions, which saw a large increase after the information.	Social, technological, and geophysical uncertainty.	Non-significant Amplification: Information did not have an amplification or weakening effect.
Green hydrogen	High-to-Moderate: Started with high acceptance/support and affect, ranking second, and maintained this position despite a drop in acceptance/ support and affect after information.	Low-to-Moderate: Started with relatively low perceived uncertainty, which saw a large increase post-information, especially for geophysical, social and economic uncertainties.	Social and technological uncertainty, and economic uncertainty only for affect.	Modest Amplification: the information significantly strengthens the negative impact of potential uncertainty on affect.
BECCS	Moderate: Started with moderate acceptance/support and affect, ranking third, and maintained this position	Moderate-to-High: Started with moderate perceived uncertainty (highest for mitigation potential uncertainty) and saw the largest increase of all uncertainties post-	Technological, social, and geophysical uncertainty, and economic uncertainty only for affect.	Modest Amplification: the information significantly strengthens the negative impact of social uncertainty on acceptance/support.

	despite a significant drop in acceptance/ support and affect after information.	information.		
Sustainable diets	Low: Started as the least popular measure and remained so, with acceptance/ support and affect near midpoint. Acceptance/ support and affect decreased slightly after information.	High: Started with the highest perceived uncertainty (especially for mitigation potential and social uncertainty), with only a slight increase post-information, especially for social uncertainty .	Technological, social, and potential uncertainty, and economic only for acceptance/support	Modest Amplification: the information significantly strengthens the negative impact of social uncertainty on acceptance/support. In contrast, the negative influence of technological uncertainty on affect was significantly weakened.



References

1. Dunn OJ. Multiple Comparisons Among Means. *Journal of the American Statistical Association*. 1961;56(293):52-64. doi:<https://doi.org/10.1080/01621459.1961.10482090>
2. Shaw M, Rights JD, Sterba SS, Flake JK. r2mlm: An R package calculating R-squared measures for multilevel models. *Behav Res Methods*. 2023;55(4):1942-1964. doi:[10.3758/s13428-022-01841-4](https://doi.org/10.3758/s13428-022-01841-4)
3. Swim JK, Guerriero JG, Gasper K, DeCoster J, Lengieza ML. Emotions and policy information predicting water-quality policy support. *J Environ Psychol*. 2024;98:102385. doi:[10.1016/j.jenvp.2024.102385](https://doi.org/10.1016/j.jenvp.2024.102385)
4. Prinzing M. Proenvironmental Behavior Increases Subjective Well-Being: Evidence From an Experience-Sampling Study and a Randomized Experiment. *Psychol Sci*. 2024;35(9):951-961. doi:[10.1177/09567976241251766](https://doi.org/10.1177/09567976241251766)
5. Nakagawa S, Schielzeth H. A general and simple method for obtaining R2 from generalized linear mixed-effects models. *Methods Ecol Evol*. 2013;4(2):133-142. doi:[10.1111/j.2041-210x.2012.00261.x](https://doi.org/10.1111/j.2041-210x.2012.00261.x)

