ADVANCING EARTH AND SPACE SCIENCES

Earth's Future

RESEARCH ARTICLE
10.1029/2025EF007697

Barrier or Enabler? Cross-Cultural Evidence on Cognitive Biases in Climate Protection

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Key Points:

- Using a stated preference approach, we investigate whether cognitive biases are negative predictors of climate change mitigation behavior
- Cognitive biases can predict climate change mitigation stated behavior; however, they do so only in a minority of cases
- Cognitive biases are not necessarily negative predictors, but can also, dependent on the context, be positive

Supporting Information:

Supporting Information may be found in the online version of this article.

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Citation:

Moser, D., Vance, C., Collard, J., Rieger, M., Anggraini, E., Merico, A., & Schlüter, A. (2026). Barrier or enabler? Cross-cultural evidence on cognitive biases in climate protection. *Earth's Future*, *14*, e2025EF007697. https://doi.org/10.1029/2025EF007697

Received 12 NOV 2025
Accepted 26 JUN 2026

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Abstract There is widespread speculation that cognitive biases pose severe barriers for humankind's ability to engage in climate change mitigation. However, the real-life significance of such effects is a matter of debate, and is likely to be subject to the bias-modifying factor culture. The claims nonetheless imply a testable hypothesis: higher levels of cognitive biases should be predictive for lower willingness to pay (WTP) for climate change mitigation measures in a variety of settings including revealed or stated preference approaches. This study tests this hypothesis using a stated preference approach with university students from Germany and Indonesia. Our analysis proceeds in two steps, beginning with measuring four cognitive biases in each participant using a battery of pre-tested psychological scales. We subsequently implement a contingent valuation experiment eliciting WTP to mitigate sea level rise, allowing us to examine how WTP varies with the extent of cognitive bias. The results provide limited support for the hypothesis. Two of the four biases examined—Risk-Seeking in Losses and Present Bias—do not significantly predict WTP. Loss Aversion is a (moderate) negative predictor in the German sample, whereas Positive Illusion is a positive predictor in the Indonesian sample. Summarily, cognitive biases predict mitigation behavior; however, only in a minority of cases, and where they do, the prediction does not necessarily have to be negative. These results suggest that the impacts, if any, of cognitive biases are complex and context-dependent, warranting careful case-by-case investigation.

Plain Language Summary Effective climate change mitigation relies heavily on behavioral changes amongst individuals. However, human behavioral patterns, as shaped throughout evolution, are generally believed to be ill-prepared for this challenge: humans generally prioritize immediate, urgent threats over slow-paced, gradually evolving large threats and humans are generally reluctant to make decisions requiring immediate sacrifices for uncertain future gains. This has led to widespread speculation that cognitive biases impede climate action. If this speculation is true, one would expect a negative relationship between biases and the desire to support climate change mitigation. Here we test this hypothesis by examining the relationship between cognitive biases and people's willingness to contribute to climate change mitigation by conducting surveys with university students in Germany and Indonesia. We first measure to what extent each student is affected by four major cognitive biases described in the literature. We then measure how these bias levels predict decision-making with respect to their willingness to contribute money to a certain climate change mitigation program. Our results suggest that cognitive biases can influence climate action; however, they do so only in a minority of cases, and where they do, the influence does not have to be negative but can also be positive.

1. Introduction

Cognitive biases potentially act as barriers that severely limit humankind's ability to mitigate and adapt to climate change and its impacts (Beattie & McGuire, 2019; Johnson & Levin, 2009; Korteling et al., 2023; Langer, 2015; Shu & Bazerman, 2011; Swim et al., 2009). Human behavioral traits have evolved to prioritize immediate, urgent threats over slow-paced and gradually evolving large threats; moreover, humans are generally reluctant to make decisions requiring immediate sacrifices for uncertain future gains (Diggs, 2017; Gifford, 2011; Gilbert, 2006; Marshall, 2014a, 2014b). This leaves humans arguably ill-equipped to deal with climate change due to its gradual, abstract and uncertain nature.

Psychology describes behavioral traits as relatively stable, personality-specific cognitive dispositions that characterize or represent a person's "baseline" tendency for certain ways of thinking and acting (American

10.1029/2025EF007697

Validation: D. Moser, A. Schlüter
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Psychological Association, 2018a, 2018b, 2018c). How a person actually behaves ultimately also depends on other, situational determinants (i.e., a context). If people show certain cognitive dispositions for a respective bias as part of their personal traits, this could lead to a correspondingly more or less biased behavior, depending on the context. The above claim that humans are ill-equipped to deal with climate change is based on the rationale that challenges posed by climate change provide a context in which human bias dispositions, as they have developed during the evolution of the brain, lead to highly biased decision making, posing barriers to effective climate action. These barriers—so the claim—cannot be easily overcome: as personal traits are stable long-term thinking and acting dispositions, individuals cannot simply change them, even if they acknowledge rationally, that the challenge they face, climate change, provides a context in which their bias dispositions lead to counter-productive, biased behavior. This alleged restriction of humankind's climate action capabilities by its own evolutionary behavioral dispositions has been coined by Johnson and Levin (2009) as "the tragedy of cognition."

Previous theoretical work linking cognitive biases and climate change mitigation has focused on how psychological traits could potentially counteract an individual's willingness to adopt mitigation behavior. This literature postulates that traits such as positive illusion, present bias, loss aversion, and risk attitude when choosing among potential losses may lead to systematic misperceptions of environmental change, potentially limiting people's ability to engage in effective climate mitigation, despite being knowledgeable about the climate change problem (Beattie & McGuire, 2019; Center for Research on Environmental Decisions, 2009; Clayton et al., 2015; Gifford et al., 2018; Gifford, 2011; Johnson & Levin, 2009; Ross et al., 2016; Schill et al., 2019; Shu & Bazerman, 2011; Swim et al., 2009; van der Linden et al., 2015—see Text S1 in Supporting Information S1 for Background Information). Indeed, a general perception has emerged in both the scientific community and the popular press that cognitive biases present severe obstacles to environmental action (Atkinson & Jacquet, 2021). However, Atkinson and Jacquet (2021) caution that such a view may, in part, be based on overgeneralisations and argue that there can be significant variations in psychological responses toward climate change within and between populations. Other scholars concur that any impact of cognitive biases on climate mitigation would likely be highly context dependent, requiring that investigations should be placed within cultural contexts (Heine, 2020; Hoffman, 2015; Moser et al., 2022).

The above claim of cognitive biases negatively impacting environmental action yields predictions that can be put to the test. If the claim is true, one would expect to see a negative relationship between cognitive biases and willingness to pay (WTP) in various study settings, including revealed or stated preference approaches. For our study, to detect a potential relationship with reasonable certainty, a sample size of at least 640 was deemed necessary, which, for practical reasons, argued for a stated preference rather than a revealed preference approach. Studies with the objective of obtaining the most precise values for WTP have at times used revealed preference, as it more directly reflects a real-life WTP; however, the focus of our study is not on the magnitude of WTP per se, but rather on examining whether different cognitive bias levels predict different WTP values. Considering all of the above, we used the contingent valuation method, one of the most established stated preference approaches, and followed best-practises guidelines to minimize "hypothetical bias"—a bias that would diverge stated from real-life preferences.

In our investigation, we present study participants with a hypothetical scenario to mitigate sea level rise (SLR) by reducing the carbon footprint to net zero, and subsequently measure their WTP to compensate for their own emissions. We then analyze how WTP relates to their individual cognitive biases scores. See Text S1 in Supporting Information S1 for more extensive Study Rationale.

As cultural psychology would predict that cognitive biases are modulated by cultural factors including psychological motivators (Heine, 2020; Medvedev et al., 2024; Moser et al., 2022), we chose to conduct our study in two culturally different regions of the world: Germany and Indonesia. To control as much as possible for background variables in this setting, we limited our study participants to university students, which are a generally utilized sample population in psychological and behavioral economic studies requiring homogeneity.

We focused our attention on positive illusion (PIBS), risk-seeking in losses (RRP), loss aversion, and present bias because of their predicted relevance on human behavior in relation to environmental action (Beattie & McGuire, 2019; Johnson & Levin, 2009; Shu & Bazerman, 2011) and we investigated whether these cognitive biases predict levels of WTP to mitigate SLR. The analysis proceeded in two steps. In the first step, we conducted surveys aiming at quantifying the four cognitive biases using a battery of established psychological scales. In the second step, we ran a binary choice experiment that randomly presented respondents with one of three bid levels

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to avoid SLR, the results from which were used to elicit their WTP via a logit model. The resulting framework allowed us to quantify how WTP varies with the extent of cognitive biases.

Our results indicate the relationship between cognitive biases and mitigation behavior is not straightforward as predicted by most literature. From this perspective, the study results should be understood as a call for further context-specific investigations, to enable policy-makers to jointly manage this gigantic global task and to assist in solving the climate challenges we are currently exposed to.

2. Materials and Methods

2.1. Data Collection

Data was collected in 2022–2023 using an online Limesurvey questionnaire. Four cognitive biases serve as our key explanatory variables: present bias, positive illusion (PIBS), loss aversion, and risk-seeking in losses (RRP). These were measured using a collection of various pre-tested psychological methods from the literature (see Table 1). Mitigating behavior, our dependent variable defined as someone's willingness to pay for measures that would mitigate climate change and its consequences, was elicited using a dichotomous choice contingent valuation approach.

We limited our respondent groups to university students from both countries for the following reasons: First, cognitive biases are culturally embedded. We accounted for this effect by testing the hypothesis in two culturally distinct locations; however, this cross-cultural setting also called for a sample setting generally accepted for cross-cultural studies, controlling background variables as much as possible and obtaining as close to a homogenous sample as possible (Hofstede, 2001). Second, our study design has to be optimized for testing the hypothesis that cognitive biases impede willingness to mitigate climate change. Such testing is ideally done in an as homogenous sample as possible, since demographic variations would introduce various factors influencing levels of biases. For example, Gächter et al. (2022) show that income positively correlates with loss aversion while education negatively correlates with loss aversion. Third, since Johnson and Levin (2009) argue that cognitive biases are barriers to environmental action in addition to mere knowledge gaps (i.e., that they materialize particularly in people who have the necessary knowledge to assess the challenges of climate change), we felt it appropriate to test the hypothesis in a population with a universal higher education. The choice of university students as participants limits the scope of our study and its interpretation. The results obtained in our study only allow to test the hypothesis that human's differences in bias levels are predictive of corresponding differences in willingness to engage in climate mitigation. The results do not represent a comprehensive analysis of absolute levels of engagement willingness across the whole population, nor a comprehensive analysis of the different cultures (compare Section 5).

Student recruitment in Germany was performed in partnership with Bremen Research and Policy Lab (BreLAB) at three universities located near the German coast: University of Bremen (Uni-Bremen), University of Applied Science Bremen (Hochschule Bremen), and University of Applied Science Bremerhaven (Hochschule Bremerhaven). In Indonesia, we recruited students from Institut Pertanian Bogor/IPB University in Bogor. Recruitment involved both physical and technological contacts by: going to University campuses, disseminating information via word of mouth, placing posters and distributing flyers in high traffic areas. Social media and other communication channels were utilized. During recruitment we explained the three eligibility criteria for participation: participants had to be (a) registered students from near coastal universities, (b) first-time participants, and (c) culturally affiliated with Germany and Indonesia. A snowballing method was also used, encouraging participants to refer others to our study. Further details of the recruitment strategy are found in Text S2 of Supporting Information S1. Bremen was chosen as recruitment location for Germany since it is the most exposed coastal German state to SLR with 92% of all its inhabitants at risk (Sterr, 2008). Indonesia, being the largest archipelago nation, is extremely vulnerable to climate change and SLR. IPB University is one of the largest universities in Indonesia with a student population from across Indonesia and with research focusing on climate risk and opportunity management. The online questionnaire was administered either during online zoom or physical meeting room sessions. This allowed participants to ask for clarifications regarding the questionnaire or the process. Every student was paid 15 Euro (in Germany) or 75,000 Rupiah (in Indonesia) for participation. Additionally, to motivate completion of the questionnaire (to reduce the number of invalid data sets due to missing data), a raffle was established through which students who successfully completed the questionnaire could win 50 Euro or 200,000 Rupiah.

The minimum sample size of questionnaires for each project site was determined to be 640 (see Text S3 in Supporting Information S1 for power analysis). Of an initial total sample of 684 students from Germany and 765 students from Indonesia, 22 German and 26 Indonesian students were deleted either due to missing data, or, in two cases (one in each country), due to very extreme outlier data. A total of 662 students from Germany and 739 students from Indonesia were included in the data analysis.

The demographics of the student sample were as follows (details see Text S10 in Supporting Information S1): Two-thirds of students were female in Germany and Indonesia. More than 90% in both Germany and Indonesia were below 30 years old. Slightly more than 50% in each country sample identified as “medium income”; less than one-third identified with “high income” and an even smaller minority with “low income.” These factors were included in the specification for models 1–3 in our analyses (see Section 2.3 for details).

Awareness of climate change in the general population is high in both countries (Gillreath-Brown et al., 2023; Leiserowitz et al., 2023). With respect to our student sample, the vast majority in both countries, 85% in Germany and 75% in Indonesia, “strongly agree” that climate change is an essential threat, and less than 5% disagree. The high awareness amongst students aligns with that of the general populations. Students were recruited across all faculties, resulting in a slight majority of participants with a predominately natural science background (70% in Indonesia and 52% in Germany respectively) and the remainder of the students with a more mixed or social science background.

2.2. Measurement of Variables

To test the claim that cognitive biases as described in psychology as individual psychological traits would be negative predictors of willingness to engage in climate mitigation, we used well-established methods to quantify, on an individual level, (a) the cognitive bias traits and (b) the willingness to engage in mitigating behavior.

A description of each bias and measurement-methodology is presented in the following subsections.

2.2.1. Measurement of Positive Illusion

According to Taylor and Brown (1988), *positive illusion* is a multifaceted cognitive bias that describes the extent to which people perceive an unrealistically optimistic view of their capabilities and ability to control events, as well as an overly positive view of the future. Methods have been established to measure the various facets of positive illusion on the group level (see Helweg-Larsen & Shepperd, 2001; Joshi & Carter, 2013; Shepperd et al., 2013, 2015 for more details). We sought out a robust method for measurement at the individual level. We chose the Positive Irrational Belief Scale (Collard & Fuller-Tyskiewicz, 2020), first developed by Collard et al. (2016), with slight adaptation devised during pretesting rounds to ensure better cultural fit (description of slight adaptation provided in Text S4 of Supporting Information S1). The Positive Irrational Belief Scale is shown in Text S4 in Supporting Information S1 and consists of a battery of statements participants agree or disagree with on an 11-point Likert scale. A Positive Irrational Belief Score, or PIBS, is created to represent the total level of positive irrational belief (i.e., positive illusion) in a person. The calculation of PIBS is a two-step process and is described in detail in Text S4 of Supporting Information S1.

2.2.2. Measurement of Risk Perception Bias

Kahneman and Tversky (1979) developed Prospect Theory describing multiple behavioral tendencies which deviate from Expected Utility Theory as proposed by neo classical economics. We chose “risk-seeking in losses” and “loss aversion,” as both describe how people behave in domains of losses, and are thus relevant for one's willingness to pay for measures to mitigate SLR.

2.2.2.1. Measurement of Loss Aversion

Typically phrased as “losses loom larger than gains”, loss aversion describes how over-averse someone is to losses in relation to gains.

Following Wang et al. (2016a) and Tversky and Kahneman (1992), we measure loss aversion using two lottery-style questions that were slightly adapted for our study. An individual's loss aversion, defined as parameter theta, θ, is calculated for each of the two lottery style scenarios, and then averaged. Larger theta values reflect larger loss

Table 1
Variables Investigated Including Standardized Method Used

Variables	Established Method/Technique Including Source
Positive Illusion	Positive Irrational Belief Scale (Collard & Fuller-Tyskiewicz, 2020)
Risk-Seeking in Losses (Prospect Theory)	Relative Risk Premium Approach (Rieger et al., 2011, 2015, 2017)
Loss Aversion (Prospect Theory)	Loss Aversion Theta Parameter Approach (Wang et al., 2016a)
Present Bias	Quasi-Hyperbolic Discounting Model (Wang et al., 2016b)
Dependent Variable: Mitigating Behavior	Single Bounded Dichotomous Choice Contingent Valuation (Johnston et al., 2017)

aversion, and vice-versa. The exact formulation of the two questions used, as well as a detailed description of the calculations used to determine a person's theta are provided in Text S5 of Supporting Information S1. To ensure equivalent cross-country comparisons, monetary values presented in Euro to German students were converted into Indonesian Rupiah for our Indonesian students using The World Bank Group (2022) Purchasing Power Parity (PPP) conversion rates, and subsequently rounded those values to the nearest 1000 currency unit. This monetary conversion approach was also taken to values involved in measuring two other bias variables: risk-seeking in losses, and present bias.

For our regression analyses, we convert this theta variable into a ranked variable using ranked regression. The highest rank is assigned the largest theta value and tied elements are averaged (Becker et al., 1988). This approach addresses potential outliers while simultaneously keeping the integrity of the original data. For example, if two theta values are equal and are ranked in 2nd and 3rd positions, then both receive a rank of 2.5.

2.2.2.2. Measurement of Risk-Seeking in Losses

Risk-seeking in losses describes a tendency where people when faced with potential losses that threaten their status quo are willing to engage with and take on more risk than usual in hopes of avoiding losses altogether (Kahneman & Tversky, 1979; Turk, 2024).

The tendency that people are risk-seeking in losses is measured using the robust Relative Risk Premium (RRP) approach applied by Rieger et al. (2015), which involves two lottery-style questions that were slightly adapted for our study context. An individual's RRP is calculated for each of the two lottery style scenarios, and then averaged. Lower RRP values denote greater tendency to be risk-seeking in losses, and vice-versa. The exact formulation of the two questions used, as well as a detailed description of the calculations used to determine a person's RRP are provided in Text S6 of Supporting Information S1.

2.2.3. Measurement of Present Bias

Present bias is a form of time inconsistent preference in which a person values immediate rewards more than future rewards, even if the expected value of the immediate reward is less than that of the future reward. Present biases have been studied extensively in various fields of Finance, Business and Economics. We adopted the methodology of Wang et al. (2016b), with slight adaptation of the two “matching” questions used to elicit a person's present bias for our study context. Participants were asked what amount of money they need to receive in 1- or 10-year' time such that this chosen amount is viewed as identically attractive as an immediate reward of 50 Euro (or Rp. 322.000 in Indonesia). A person's present bias, symbolized as parameter β, is then calculated using participant answers from both questions and formulae based on the quasi-hyperbolic discounting model. The larger β, the less present bias. The exact formulation of these two survey questions, and the formulae used to calculate a person's present bias are provided in Text S7 of Supporting Information S1.

2.2.4. Measurement of Mitigating Behavior

To derive the willingness to mitigate climate change at a certain price by supporting (i.e., saying yes to) a proposal to implement a carbon-price scheme, we employ a stated preference method known as contingent valuation, which is a useful tool to evaluate people's preferences for non-market resources (Boyle, 2017; Haab et al., 2020; OECD, 2018).

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Our design followed best-practice recommendations from the updated U.S National Oceanic and Atmospheric Administration (NOAA) Panel Guidelines established by Johnston et al. (2017),Boyle (2017), and Haab et al. (2020). These guidelines foster truthful preference revelation and they enhance the validity of value estimates. Additionally, they address concerns over hypothetical bias, strategic behavior, incentive compatibility, and framing effects. For example, we integrate two enhancement techniques: an ex ante cheap talk script, adapted from Ladenburg et al. (2010) and Sonnenschein and Mundaca (2019), as well as an ex-post certainty approach question (Blomquist et al., 2008). An ex ante cheap talk script reminds participants to elicit truthful answers by imagining the scenario to be real and that the choices they make have real cost implications on them, despite the hypothetical nature of the stated preference approach. The ex-post certainty approach asks participants explicitly how certain they are about their choices. This allows us to conduct a robustness check on a sub-sample of students considered to have high certainty. Descriptions of these two techniques and exact formulation used in our survey are provided in Text S8 of Supporting Information S1. Furthermore, we use a single bounded dichotomous choice format, which is considered a preferred method in the literature as it adheres to incentive compatibility standards and offers an easy way for participants to elicit their preferences (Boyle, 1990, 2017; Boyle & Bishop, 1988; Johnston et al., 2017).

Details of the contingent valuation scenario, as well as the establishment of our bid design, are provided in Text S8 of Supporting Information S1. In summary, to elicit the bids, respondents read a scenario in which the government proposes to set a price on carbon. The price was set at one of three randomly selected values. In detail, the question reads: "Would you be willing to support this proposal if you had to pay X € per tonne CO_2 equivalent (tCO2e)?" where X is randomly replaced with either 15€, 50€, and 150€ for the German context, or Rp 96.000, Rp 322.000, Rp. 965.000 for the Indonesian context. As people often struggle to quantify the amount of CO_2 they produce, we provided two reference points to aid their decision-making: (a) the average person's carbon footprint, and (b) the carbon footprint of an eco-friendly lifestyle person in the respective country. The exact formulation of these two reference points is provided in Text S8 of Supporting Information S1.

2.2.5. Measurement of Socio-Economic Variables

Non-cognitive variables, such as age, income, and gender, are key socio-economic factors that may prove influential. Age and income were gathered with categorical variables to reduce the amount of potential missing data responses. As some students may not have a "formal" income, but are supported either by government or parents, we asked them how much money they typically have available for spending per month. In addition to these aforementioned variables, we investigate how different perspectives on the "nature of nature" may influence mitigating behavior, as one's view on nature is related to one's environmental concern. Specifically, the "nature of nature" concept refers to four different viewpoints about nature: capricious, benign, ephemeral, and tolerant/perverse (Gifford & Nilsson, 2014).

2.3. Econometric Approach

Following Buckland et al. (1999, p. 110), the logistic regression represents "the natural way to analyze dichotomous choice", and was consequently used to analyse the relationship between mitigating behavior and cognitive biases for both country data sets. The econometric approach used to analyse the single bounded dichotomous choice answers and estimate mean WTP values is similar to Frondel et al. (2019), which follows earlier contributions by Bishop and Heberlein (1979), Buckland et al. (1999), Hanemann (1984) and Hanemann and Kanninen (2001).

We estimate three logistic regression models, starting with a parsimonious model that estimates the effect of the bid, the key explanatory variable, along with a set of socio-economic variables denoted as x_i (see Model 1). Model two introduces measures of the four cognitive biases, revealing whether controlling for these biases bears on the estimate of the bid. Our main focus is on model three, which includes interaction terms between the bid values and each of our four biases (referred thereafter as bid-bias interaction terms), thereby allowing us to explore whether the effect of the bid varies by the level of bias.

$$\text{Model 1: } \Pr(Y_i = 1|\text{bid}_i, x_i) = \Lambda\left[\widehat{\beta_0} + \widehat{\beta_1}\ln(\text{bid}_i) + \widehat{\beta}_x x_i\right]$$

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$$\text{Model 2: } \Pr(Y_i = 1|\mathrm{x}) = \Lambda\Big[\widehat{\beta_0} + \widehat{\beta_1}\ln(\mathrm{bid}_i) + \widehat{\beta_2}\mathrm{PresentBias} + \widehat{\beta_3}\mathrm{PIBS} + \widehat{\beta_4}\mathrm{RRP} + \widehat{\beta_5}\mathrm{LossAversion} + \widehat{\beta}_x x_i\Big]$$

$$\begin{aligned}\text{Model 3: } \Pr(Y_i = 1|\mathrm{x}) = \Lambda\Big[&\widehat{\beta_0} + \widehat{\beta_1}\ln(\mathrm{bid}_i) + \widehat{\beta_2}\mathrm{PresentBias} + \widehat{\beta_3}\mathrm{PIBS} \\ &+ \widehat{\beta_4}\mathrm{RRP} + \widehat{\beta_5}\mathrm{LossAversion} + \widehat{\beta_6}\ln(\mathrm{bid}_i)\times\mathrm{PresentBias} \\ &+ \widehat{\beta_7}\ln(\mathrm{bid}_i)\times\mathrm{PIBS} + \widehat{\beta_8}\ln(\mathrm{bid}_i)\times\mathrm{RRP} \\ &+ \widehat{\beta_9}\ln(\mathrm{bid}_i)\times\mathrm{LossAversion} + \widehat{\beta}_x x_i\Big]\end{aligned}$$

For all three models, Y_i is a binary indicator that equals unity if respondent i is willing to pay either 15€, 50€, or 150€ (Germany), or Rp 96.000, Rp 322.000, or Rp. 965.000 (Indonesia), and equals 0 otherwise. Λ represents the logistic cumulative distribution function, where the bid amount (i.e., price for carbon suggested in this hypothetical market) is included in log terms. A logarithmic transformation of the bid amounts is conducted per Buckland et al. (1999)'s recommendation to more accurately analyze the dichotomous choice data and model the WTP curve better, thus increasing accuracy of mean WTP estimations. This log transformation ensures WTP estimates are non-negative, which is (a) beneficial as negative WTP values can be problematic for analytical purposes (Haab & McConnell, 1997), and (b) considered appropriate in this case, as the public good should not be considered to provide a person disutility.

We use the following formula to estimate the mean WTP values (Frondel et al., 2019; Hanemann, 1984):

$$\begin{aligned}E[\mathrm{WTP}_i] = \int_0^{\infty}\Big\{1 - \Lambda\Big[&\widehat{\beta_0} + \widehat{\beta_1}\ln(\mathrm{bid}_i) + \widehat{\beta_2}\mathrm{PresentBias} + \widehat{\beta_3}\mathrm{PIBS} \\ &+ \widehat{\beta_4}\mathrm{RRP} + \widehat{\beta_5}\mathrm{LossAversion} + \widehat{\beta_6}\ln(\mathrm{bid}_i)\times\mathrm{PresentBias} \\ &+ \widehat{\beta_7}\ln(\mathrm{bid}_i)\times\mathrm{PIBS} + \widehat{\beta_8}\ln(\mathrm{bid}_i)\times\mathrm{RRP} \\ &+ \widehat{\beta_9}\ln(\mathrm{bid}_i)\times\mathrm{LossAversion} + \widehat{\beta}_x x_i\Big]\,\mathrm{dbid}_i\end{aligned} \tag{1}$$

We integrate up to the highest bid of €150 or Rp. 965.000 respectively, rather than integrating up to infinity, to avoid obtaining unreasonably high estimates of mean WTP values (Bishop & Heberlein, 1979; Hanemann, 1984; Hanemann & Kanninen, 2001). This approach is in line with the NOAA Panel's recommendation to prefer a conservative estimate over an estimate that risks being too large (Arrow et al., 1993).

Model 3 provides the essential answers to our hypothesis testing. It allows us to investigate differential effects of cognitive biases on mitigation behavior by measuring how WTP differs per level of bias, holding other factors fixed. To achieve this, we input various values that fall within the range of each bias (e.g., mean value, minimum value, etc.) for each student sample into Model 3, and run a bootstrap with 1000 iterations to calculate respective WTP and standard error. Analysis was conducted in R (R Core Team, 2023) using the following packages: "foreign" (R Core Team, 2022), "rio" (Chan et al., 2021), "MASS" (Venables & Ripley, 2002), "stats" (R Core Team, 2023), "boot" (Canty & Ripley, 2022; Davison & Hinkley, 1997), "huxtable" (Hugh-Jones, 2022). See Text S9 of Supporting Information S1 for R code used and raw R console results for all three models. Finally, how WTP differs per level of bias was plotted visually including a line of best fit (Figures 2 and 3, and Text S12, Figures S1 and S2 in Supporting Information S1). Graphic display was produced with the assistance of ChatGPT-o4-mini-high and ChatGPT-5.

2.4. Qualitative Data

In addition to quantitative data, we also collected qualitative data to aid interpretation and extend our quantitative findings with specific rationales in the form of direct quotes. We asked every respondent the closed form question "Do you think that in principle we will get the causes of sea level rise under control or not?" to which they answered either "Yes" or "No." Subsequently, they were asked in open-ended format to elaborate and explain why they answered "Yes" or "No." The aim of this approach was not to conduct an exhaustive comprehensive qualitative content analysis, but rather to capture concisely common grounds of reasons and rationales for these answers.

3. Results

A total of 662 and 739 complete data sets from Germany and Indonesia respectively were subjected to quantitative and qualitative analysis. The quantitative analysis consisted of descriptive statistics and regression Models 1–3. The qualitative data from both the closed and open-ended questions were analyzed according to Section 2.4 as shown in Text S13 of Supporting Information S1; the closed-ended questions per se were analyzed for mean level of each cognitive bias in Text S14 of Supporting Information S1.

3.1. Descriptive Statistics

Figure 1 compares the mean levels of four cognitive biases—present bias, risk attitude in losses, loss aversion, and positive illusion—between Germany and Indonesia, revealing both differences in the average strength of cognitive biases and the degree of variability in how those biases manifest across countries. The mean present bias is higher in Indonesia, and the 95% confidence intervals (CIs) do not overlap with those of Germany, suggesting a statistically significant difference (panel a). We likewise see statistically significant differences with respect to both risk attitude in losses and positive illusion in panels b and d. Note that when we refer to risk-seeking attitude in losses, we are not suggesting they seek risk per se, but rather their willingness to engage in more risk than usual in the hopes of avoiding potential losses altogether. The negative magnitude of risk attitudes is higher in Germany and the positive magnitude of positive illusion is higher in Indonesia. Error bars for loss aversion in Indonesia are noticeably large due to two datapoints that may arguably be considered outliers. If they were to be removed, the error bars are of similar size as that of Germany. An explanation for the two outliers is not immediately evident; we speculate that it may relate to the significant variation in socio-economic conditions, education quality, and cultural norms across Indonesia's highly diverse landscape, even among university students. The large error bars due to these datapoints are of no concern as it is accounted for in our regression analyses having conducted a ranked regression.

The results for socio-economic variables are presented in Text S10 of Supporting Information S1.

3.2. Regression Results

The general notion that cognitive biases hinder environmental action would suggest a negative relationship between cognitive biases and people's willingness for action. In the following we put this hypothesis to the test.

We first investigate the direct effect of the bid variable on mitigating behavior (Model 1, Tables 2 and 3). We then check whether the inclusion of bias variables has a bearing on our estimate of the bid (Model 2, Tables 2 and 3) and thus the willingness to pay (WTP) amount (Table 4). This allows us to determine whether biases affect WTP in general. Subsequently, we investigate the differential effect of the bias variables on WTP (Model 3, Figures 2 and 3). This allows us to specifically discover the extent to which each bias affects willingness for environmental action.

In line with conventional expectations, the German and Indonesian students exhibit a significant negative relationship between the bid value (i.e., carbon price) and the willingness to engage in mitigating behavior (Model 1, Tables 2 and 3). This significant negative relationship remains after we include all four bias variables (Model 2, Tables 2 and 3). Such a result reflects standard economic theory that the demand for a good typically decreases as the price of the good rises. Furthermore, although it seems that certain biases are significant in Model 2 (i.e., "risk-seeking in losses" and "loss aversion" in Germany, Table 2, and "positive illusion" in Indonesia, Table 3), the inclusion of our four biases in Model 2 does not seem to have an enormous bearing on coefficient estimates and standard error values.

To further facilitate interpretation, Table 4 presents estimates of the WTP derived from the coefficient on bid from Models 1 and 2 for Germany and Indonesia. Three estimates of WTP are presented: in the original currency, in euros using the exchange rate, and in euros using the purchasing power parity adjustment. When expressed in the original currency, we see that all the estimates are individually statistically significant but that they do not vary

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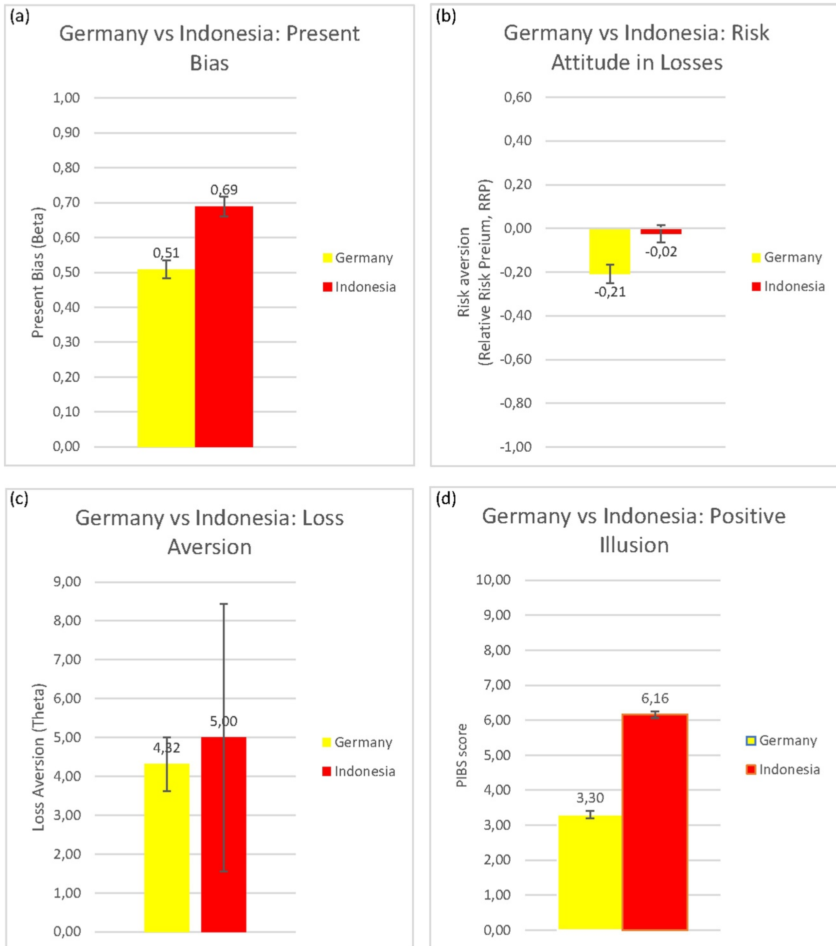

Figure 1. Mean Level of Present Bias (a), Risk Attitude in Losses (b), Loss Aversion (c), and Positive Illusion (d) in German and Indonesian Sample Population, including 95% CIs.

significantly between Models 1 and 2. Turning to the exchange rate adjusted estimates, the WTP to mitigate SLR amounts to about 59 euros among German students, over double the 27 euros estimated for Indonesian students. Interestingly, this ranking is reversed when using PPP-adjusted figures: The WTP among Indonesian students is in this case about 73 euros, nearly 20% higher than the WTP of German students. This reversal likely reflects the fact that the purchasing power of a euro is substantially higher in Indonesia than in Germany. When using exchange rates, Indonesian WTP appears lower because nominal incomes are lower; however, when adjusted for local price levels via PPP, the same nominal amount buys more goods and services in Indonesia, revealing a higher real WTP.

To allow for differential effects of the bid by the level of cognitive bias, Model 3 includes the interaction of the bid with each type of bias (Tables 2 and 3). For both the German and Indonesian sample, this specification reveals that the negative effect of the bid is exacerbated by the level of present bias. Put alternatively, the WTP decreases as present bias increases. For the Indonesian sample, we additionally see that the negative effect of the bid weakens with increases in positive illusion bias, suggesting higher WTP as this source of bias increases.

Figures 2 and 3 present these results and those corresponding to the other biases graphically, including both the point estimates and the 95% CIs for different levels of bias (n.b. the larger the *x*-axis value for present bias and risk-seeking in losses, the smaller the bias; the larger the *x*-axis value for loss aversion and positive illusion, the larger the bias). Most of the graphs give rise to a linear pattern, reflecting a consistent directional relationship between the level of bias and the WTP, in line with the modest magnitude of interaction effects and the smoothness of the underlying relationship. Two additional features of the graphs stand out. First, the WTP is in all

Table 2
Logistic Regression Results for the German Sample

	Model 1	Model 2	Model 3
(Intercept)	3.130 *** (0.400)	3.912 *** (0.513)	1.271 (1.322)
Bid (i.e. Carbon Price)	−0.874 *** (0.095)	−0.893 *** (0.097)	−0.182 (0.347)
Present Bias (PB)	–	−0.120 (0.264)	3.357 ** (1.162)
Positive Illusion (PIBS)	–	−0.056 (0.062)	−0.087 (0.253)
Risk-Seeking in Losses (RRP)	–	0.339 * (0.165)	−0.174 (0.710)
Loss Aversion (LA)	–	−0.001 * (0.000)	0.002 (0.002)
Bid x PB	–	–	−0.930 ** (0.304)
Bid x RRP	–	–	0.139 (0.184)
Bid x LA	–	–	−0.001 (0.001)
Bid x PIBS	–	–	0.008 (0.067)
Control Variables	Yes	Yes	Yes
N	662	662	662
loglik	−400.101	−393.029	−387.021
AIC	820.203	814.058	810.042

Note. The full set of results is presented in Text S9, Table S1 of Supporting Information S1. Standard errors are reported in parentheses. Bid represented as ln value of carbon price (see Section 2.3). ***p < 0.001; **p < 0.01; *p < 0.05; · p < 0.1.

cases itself highly statistically significant, as the CIs fall well above zero. Second, the differences in WTP at different levels of a given bias are in general not statistically significant, as evidenced by the overlap of the CIs with each other. One exception to this pattern pertains to the estimates of loss aversion in the German sample: at the far extremes, the WTP among the highest level of loss aversion is lower than at the lowest level. Another exception is seen for the estimates of positive illusion from the Indonesian sample. In this case we see significantly higher estimates of WTP among those with the highest levels of positive illusion compared with the mean and lowest level.

Table 3
Logistic Regression Results for the Indonesian Sample

	Model 1	Model 2	Model 3
(Intercept)	3.548 *** (1.036)	3.090 ** (1.119)	6.481 (5.554)
Bid (i.e. Carbon Price)	−0.308 *** (0.081)	−0.310 *** (0.082)	−0.584 (0.441)
Present Bias (PB)	–	−0.172 (0.197)	7.168 ** (2.662)
Positive Illusion (PIBS)	–	0.132 * (0.060)	−1.557 · (0.817)
Risk-Seeking in Losses (RRP)	–	0.164 (0.141)	1.354 (1.921)
Loss Aversion (LA)	–	−0.001 (0.000)	0.005 (0.005)
Bid x PB	–	–	−0.583 ** (0.211)
Bid x RRP	–	–	−0.092 (0.152)
Bid x LA	–	–	−0.000 (0.000)
Bid x PIBS	–	–	0.134 * (0.065)
Control Variables	Yes	Yes	Yes
N	739	739	739
loglik	−496.664	−492.057	−485.499
AIC	1013.328	1012.113	1006.998

Note. The full set of results is presented in Text S9, Table S2 of Supporting Information S1. Standard errors are reported in parentheses. Bid represented as ln value of carbon price (see Section 2.3). ***p < 0.001; **p < 0.01; *p < 0.05; · p < 0.1.

Table 4
Models 1 and 2 Calculated Mean WTP Estimates for Both German and Indonesian Samples

		Original currency		Euro—Exchange rate adjusted[a]		Euro—PPP adjusted	
		Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Germany	Mean WTP	59.26	59.32	59.26	59.32	59.26	59.32
	Standard Error	2.79	2.81	(N/A)	(N/A)	(N/A)	(N/A)
Indonesia	Mean WTP	468068.00	468255.80	26.66	26.67	72.79	72.82
	Standard Error	17968.62	17561.59	(N/A)	(N/A)	(N/A)	(N/A)

[a]Average exchange rate for year 2021, which is the same year we use for PPP conversions, is used. Source: The European Central Bank (2024).

These results contrast the simple narrative that cognitive biases present monumental barriers that hinder environmental action in the following way: although cognitive biases may predict mitigation behavior, they do so only in a minority of cases; and where they do, the prediction does not necessarily have to be negative but can also be positive. Only two of the four cognitive biases, a different one in each country, showed an ability to predict mitigation behavior. The first one, loss aversion in Germany, is a negative predictor of WTP, albeit with a statistical significance only toward the extreme of the bias expression range. The second one, positive illusion in Indonesia, contrasting the above narrative's presumed negative predictions, is a positive predictor of WTP. The other two biases, risk-seeking in losses (RRP) and present bias, are not statistically significant predictors. Nevertheless, and given the linear-like trend between these biases and WTP, we should not rule out any underlying relationship per se, or assume that no predictions could ever be made under different circumstances.

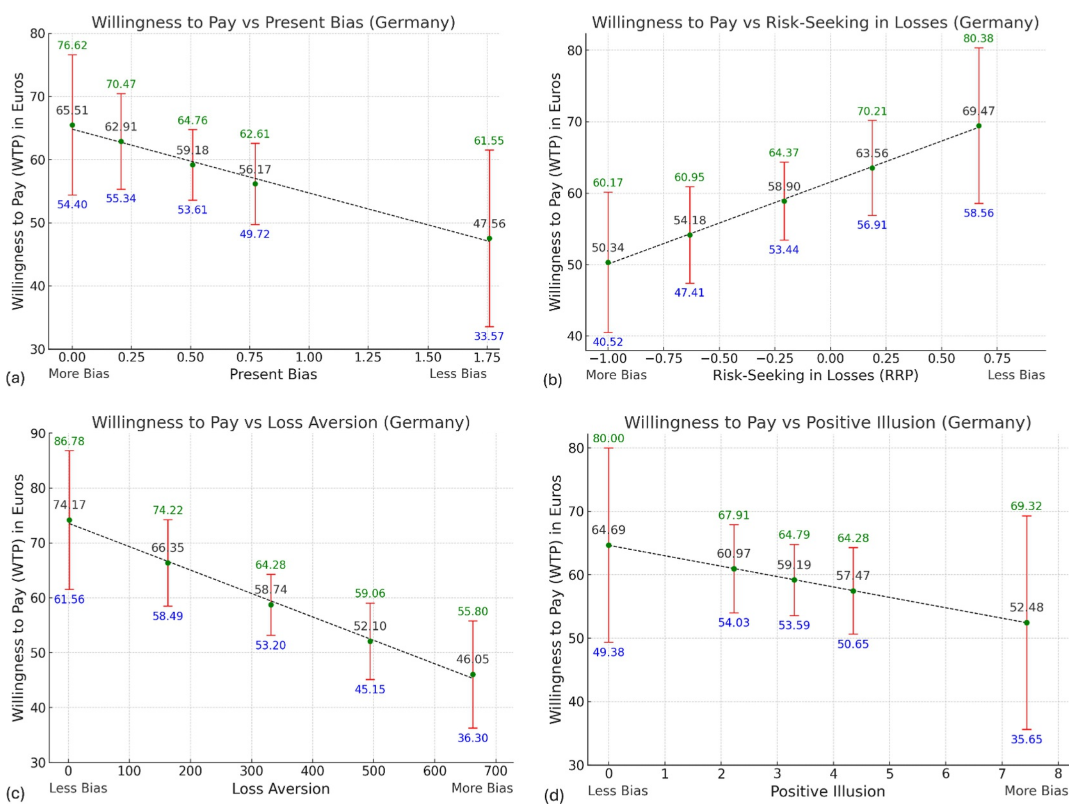

Figure 2. Changes of Willingness to Pay per level of Present Bias (a), Risk-Seeking in Losses (b), Loss Aversion (c), and Positive Illusion (d) in the German Data set, including 95% CIs.

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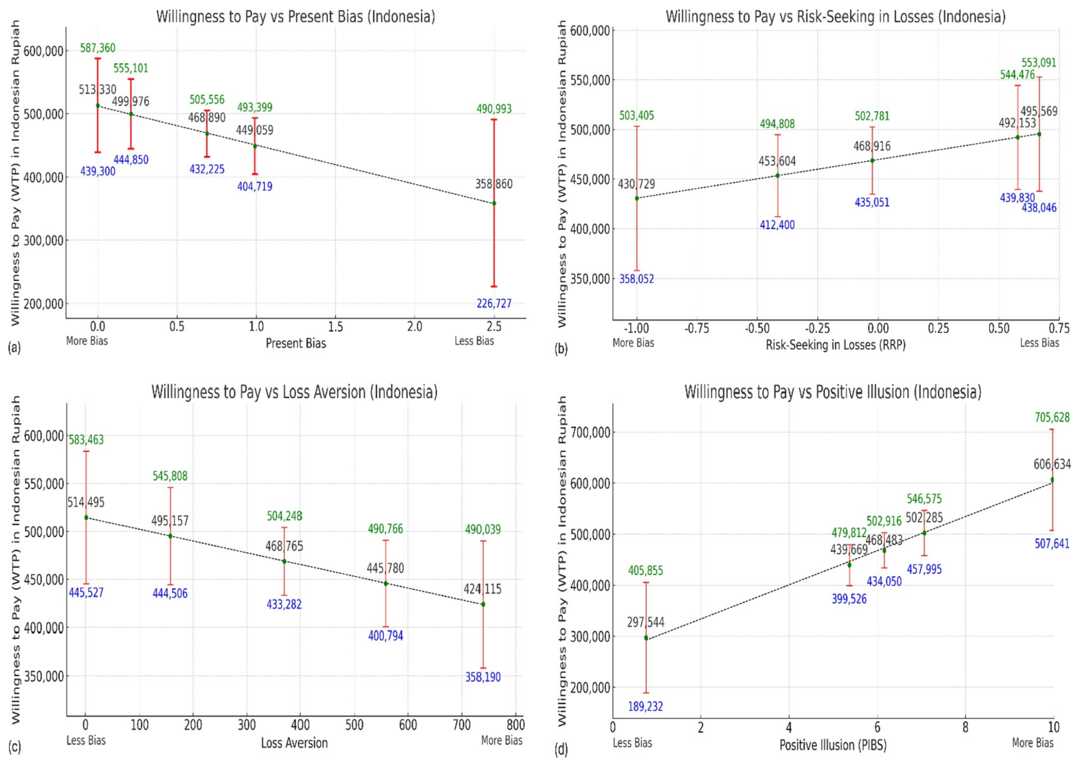

Figure 3. Changes of Willingness to Pay per level of Present Bias (a), Risk-Seeking in Losses (b), Loss Aversion (c), and Positive Illusion (d) in the Indonesian Data set, including 95% CIs.

3.3. Additional Analysis and Robustness Check

Interestingly, the significance values of $p < 0.01$ for the present bias bid-bias interaction terms in Germany and Indonesia produced with Model 3 regression (Tables 2 and 3) do not translate into significantly different WTP estimates (Figures 2 and 3). An additional analysis (Text S11 in Supporting Information S1) confirmed that the significance of this intermediate regression result has no impact on our end WTP result at 95% CI.

A robustness check was conducted to determine whether the meaning of results changes if we limit our analysis to the sub-sample of those who only answered "definitely sure" in our certainty approach question (Text S12 in Supporting Information S1). The results for the Definitely Sure subsample generally mirror the full sample results; however, due to larger standard errors caused by the small sample size, loss aversion and positive illusion did not demonstrate predictive capacities for their respective German and Indonesian subsamples (i.e., error bars are overlapping).

4. Discussion

How obstructive a barrier do cognitive biases pose to climate change mitigation action? The general notion that cognitive biases present severe barriers to climate action represents a hypothesis that can be tested. Here we chose a stated preference method to test the hypothesis. We select the most prominently mentioned biases considered to be the major culprits and rank individuals on bias scores using established standard psychological methods for psychological traits displaying a respective cognitive bias disposition. We then subject individuals to a hypothetical scenario within the context of SLR mitigation. In this context, the above-mentioned bias trait/cognitive disposition is now expected to be expressed in a climate change context-specific manner and, according to the hypothesis tested, to influence willingness to engage in SLR mitigation in a negative way. In the hypothetical scenario, participants were asked to indicate their willingness to engage in SLR mitigation by way of expressing their WTP to compensate for their own carbon emissions. We then test how bias scores predict WTP outcomes. To our knowledge, this is the first time that the above hypothesis has been tested in an empirical setting.

Cognitive biases can be predictors of willingness to engage in climate action; however, in our study population this occurs only in a minority of cases. The claim of cognitive biases being severe barriers to environmental action suggests one would expect to see a negative relationship between cognitive biases and willingness to pay (WTP) for most, if not all, of the four biases we investigated. Our study populations, German and Indonesian students, expressed a mixed pattern of generally weak relationships between biases and environmental action. Loss aversion is a significant negative predictor for people toward the extreme of the bias expression range in the German sample. Conversely, positive illusion is a positive predictor in the Indonesian sample. No significant predictions were found for the other two biases, risk-seeking in losses (RRP) and present bias.

Higher *loss aversion* is associated with lower WTP values in both Germany and Indonesia. However, a statistically significant prediction of WTP is only observed in the German sample, and only toward the extreme of the bias expression range. Theoretically, both positive and negative correlations could be possible, because the subjective reference point, which determines what is perceived to be a loss or a gain, is not uniform amongst people. Generally, loss aversion suggests that the psychological pain of a loss looms larger than the pleasure of an equivalent gain, and that people therefore prefer to avoid potential losses at the risk of failing to achieve potential gains. But what determines a possible loss or gain depends on the subjective frame of reference of individuals and what domains they think they are in, irrespective of the fact that they are in a domain of losses (UBS, 2024).

Our study was designed to ensure that all participants received identically framed reference points (see Text S8 in Supporting Information S1); however, the perception of values and outcomes of participants in the Contingent Valuation Scenario, for example, the stated carbon price and the proposed future, would not be uniformly viewed as a loss or a gain, given the mentioned inner subjective reference points that guide decision making. Consequently, if the fear of participants for an immediate negative loss due to $CO2$ compensation is weighted lower than the fear of the bigger future loss due to climate change consequences, then we would expect a positive correlation between loss aversion and WTP. If, however, the immediate loss is weighted higher, we would expect a negative correlation. The latter is what we observe in the German sample.

The observed result that loss aversion is a negative predictor in the German sample is in line with the general narrative in the literature that biases impede climate action, and it may have implications for policymakers. Since the outcome of loss aversion on decision-making is determined by subjective reference points, policymakers could aim to shift the focus of people from immediate losses to the greater future losses. Human nature generally places losses over gains in decision-making (Tversky & Kahneman, 1992; UBS, 2024). And particularly in an angst-society like Germany, fears from future losses were shown to be main drivers of successful past environmental movements (Biess, 2019). Aligning with this strategy, climate activists like Fridays for Future have indeed created greater awareness in the population for the negative future impact of climate change (Brehm & Gruhl, 2024). Our results, however, indicate that this awareness did not accomplish to shift loss aversion from any degree of hindering environmental action to promoting environmental action. Based on the literature on change management, one might argue that this outcome is not entirely surprising: While "create a sense of urgency" is indeed the first important step in initiating change, it has to be complemented by successive steps like providing a vision and a strategy clarifying "how the future will be different from the past, and how you can make this future a reality" (Kotter & Rathgeber, 2006, p. 130). The United Nations Sustainable Development Goals (United Nations, 2015) and scholars promoting the idea of "imagineering" (Metelmann & Welzer, 2020) and fostering behavioral changes based on intrinsic motivation of people (Bolderdijk et al., 2013; van der Linden, 2015) are following this path. Indeed, it might be a combination of catering to both loss aversion, by emphasizing future losses, and to intrinsic motivation to change (Bolderdijk et al., 2013; van der Linden, 2015), which might ultimately prove successful.

Cognitive biases may also be positive predictors of willingness to engage in climate action.

Positive illusion is a positive predictor of WTP in Indonesia when comparing mean- and high-biased individuals to low-biased individuals.

This result may seem unexpected, since one might argue that positive illusion would hinder environmental action, as people may underestimate climate risks, either because they are unrealistically optimistic about the future or because they believe we can anyway mitigate the risks, however severe, based on an irrational overestimation of our problem-solving ability, driven for example, by (a) self-enhancement of capabilities, (b) illusion of control, or (c) a sense of "false hope", where problems would just be sorted out by themselves without human action (Beattie

& McGuire, 2019; Gifford et al., 2018; Johnson & Levin, 2009; Marlon et al., 2019; Moser et al., 2022). Furthermore, comparative optimism drives people to underestimate their own risk exposure to environmental hazards relative to others (Pahl et al., 2005), a perception, that is, in line with downplaying the urgency to engage in environmental action.

However, one may also conversely hypothesize that positive illusion promotes environmental action, when, under apparent hopelessness, the only motivation forward is to believe that one is able to face the odds and overcome them (Atkinson & Jacquet, 2021; Bury et al., 2020; Scheier et al., 1986). Positive illusion could also promote action if it conveys "constructive hope" (rather than "false hope") and with it self-assurance for action (Marlon et al., 2019). These conceptual arguments suggest that both positive and negative effects of positive illusion are plausible. The statistically significant impact found in our study, however, is the positive effect in Indonesia.

For *present bias,* we also observe increasing WTP estimates for individuals with increasing bias in both Germany and Indonesia. This observation could be seen as supporting the above notion that biases would not always go counter to environmental action. However, no definite conclusion can be reached here due to lack of statistical evidence: WTP estimates, including standard errors, are overlapping.

Accounting for cultural contexts.

The literature suggests that cognitive biases' predictive patterns should be studied within their cultural contexts (Heine, 2020; Moser et al., 2022). Our results indeed support this notion.

The two cognitive biases which predict WTP, positive illusion and loss aversion, each did so in only one of the two countries: positive illusion was a positive predictor in Indonesia, and loss aversion a negative predictor in Germany. This finding parallels another observation in our study, that there is an approximately 20% lower WTP in the German compared to the Indonesian sample, as measured in terms of purchasing power parity.

Positive illusion showed contrasting results for Indonesia and Germany. In Indonesia, it acts as a positive predictor of WTP. In Germany, individuals with increasing positive illusion show less WTP; however, no significance across the entire range of bias is expressed. These differences suggest a cultural influence.

Positive illusion is a multifaceted bias involving inflated self-capabilities or self-enhancement, illusion of control, and unrealistic optimism (Taylor & Brown, 1988). When claiming universality or cross-cultural differences for positive illusion (and biases in general), it is vital to ensure that analyses are conducted on the same level of bias-abstraction: "evidence for universality might be clear at one level of abstraction but not at another" (Heine, 2005, p. 531). As such, the overall cultural psychology literature is diverse with respect to the effects of culture between individualistic and collectivistic societies (Chang et al., 2001; Heine, 1993, 2005, 2020; Heine et al., 2007; Heine & Hamamura, 2007; Heine & Lehman, 1995; Joshi & Carter, 2013; Klein & Helweg-Larsen, 2002; Markus & Kitayama, 1991; Rose et al., 2008). Most existing studies focus on sets of cultures in North America (US/Canada) and East Asia (Japan/China/Korea), and are based on student samples. These studies show a wide consensus that Westerners have a robust tendency to exhibit positive illusion; however, the consensus does not seem to completely extend to non-western societies. Most studies suggest lower levels of bias for Eastern societies (Heine, 2005; Heine & Hamamura, 2007; Rose et al., 2008), while Joshi and Carter (2013) find higher levels for Indian compared to English middle-class population samples.

Our results appear at odds with the observation that Eastern societies exhibit lower levels of positive illusion than Western societies. Mean levels of positive illusion are markedly higher in Indonesian relative to German students. Qualitative answers in our study help make sense of these puzzling results (Text S13 in Supporting Information S1). Positive illusion among Indonesian students seems to associate positively with their sense of human capacities to deal with climate change. In fact, 84% of Indonesian students believe we can get the drivers of SLR under control. Of this majority, many respondents state that climate change is anthropogenic and, as such, it is up to humans to change behaviors and reduce carbon emissions. Scepticism with respect to pro-environmental behavioral changes is less prevalent among Indonesians than Germans. This may be attributed to shared views amongst Indonesian students that people ought to have a sense of moral duty and personal responsibility to be good stewards of the earth and engage in mitigating behavior. This notion corresponds well with another narrative expressed amongst Indonesian students: if mitigation efforts are not undertaken, the losses would be too catastrophic; hence a sense of loss aversion is expressed with respect to future non-affordable losses. These two narratives reflect positive outcomes of positive illusion. On one hand, since the problem is anthropogenic in nature, it is also solvable through anthropogenic changes. On the other hand, if we fail to engage and mitigate climate change, the consequences would be unbearable, giving us no choice but to engage. These positive traits of positive illusion could be used to improve policymaking strategies by utilizing “constructive hope” and people's sense of empowerment to act.

There are several reasons why our Indonesian results differ from previous findings that Easterners in general exhibit less positive illusion than Westerners. Indonesia differs in many aspects from other East Asian societies. First, the country has a unique history particularly with respect to its role as a frontrunner of de-colonialization (Reybrouck, 2022). Second, the Indonesian belief system is unique given the predominately Muslim background. Third, individualism, which has been linked to higher positive illusion, may play a role. Eastern societies are generally perceived to be collectivist, rather than individualistic societies. However, a recent increase in individualism has been observed in the region as part of a global trend, with a few exceptions like China (Santos et al., 2017), which may set our study apart from previous studies in a temporal way. In Indonesia, a study on this trend revealed that Generation Z, which constitutes 94% of our sample, exhibited markedly increased traits of individualism compared to the previous generation of Millennials (Schofield, 2018).

Higher *loss aversion* is associated with lower WTP values in both Germany and Indonesia; however, loss aversion is only found to be a significant predictor in the German sample and only toward the extremes of the bias scale.

Cross-cultural differences in loss aversion have been investigated in previous works. For example, Wang et al. (2016a) showed that people from individualistic societies are more loss averse than people from collectivist societies. This result supports the “cushion hypothesis” by Hsee and Weber (1999), which stipulates that individuals from collectivist societies are generally less risk-averse and willing to accept financial risks because they can rely on support from their social network. Also Rieger et al. (2011) uncovered cross-cultural differences in loss aversion; however, they found that higher levels on Individualism Index Scores (IDV), the index associated with the individualism-collectivism cultural scale, led to lower loss aversion values. This result contradicts the cushion hypothesis. Additionally, they found cross-cultural differences along another cultural dimension, Uncertainty Avoidance—measured as Uncertainty Avoidance Index Scores (UAI). Larger levels of UAI corresponded to larger loss aversion. This is antipodal to the result of Wang et al. (2016a), who state that “UAI is not a robust predictor of loss aversion” (p. 278). Despite directional differences, these studies, along with those of Bontempo et al. (1997) and Rieger et al. (2017), who investigated cross-cultural differences in risk perceptions (of which loss aversion is an integral part), demonstrate that cross-cultural differences exist. Hence, loss aversion is culturally embedded. Our results lend support for this conclusion.

There are several possible reasons why loss aversion was not found to significantly predict WTP in the Indonesian sample. Firstly, as the association was only seen for highly biased individuals within the German sample, one would expect that slight differences in perceptions and reference points could explain the null result in Indonesia. If, for example, a slightly higher percentage of Indonesians weight the future loss greater than the immediate loss, this would shift the effect of the bias away from a purely negative association. This would be in line with our Indonesian qualitative results. As discussed, these answers seem to have a dual nature: a mere optimism of a “yes we can” spirit based on a sense of responsibility; and, conversely, a narrative that urges them to act because losses are too great to be ignored.

Secondly, one could speculate that positive illusion, which was high among the Indonesian sample, could counteract loss aversion with respect to immediate losses. Positive illusion is a coping-mechanism for negative experiences (Taylor, 1989; Taylor & Brown, 1988, 1994; Taylor et al., 1992) and therefore could be expected to mitigate psychological pain typically felt when facing or perceiving potential losses. The nature of positive illusion expressed by our Indonesian sample was such that it promoted environmental action; hence associated with a sense of empowerment and control. They also expressed in their qualitative answers a high degree of personal responsibility as “good stewards for the earth.” As such, our results are in line with a psychological effect where people are able to compensate for some of their loss aversion and become pro-environmental when feeling responsible, empowered, and in control. This could help to define concepts and narratives useful for promoting environmental action. Policymakers could use techniques that foster a sense of control and empowerment in their target population with respect to climate mitigation measures.

5. Limitations and Future Research

The design of this study limits the ability to generalize our results. Our study is limited to testing the hypothesis that cognitive biases present barriers to people's willingness to engage in climate mitigation, by investigating whether differences in bias-levels predict corresponding differences in WTP in a stated preference behavioral setting. The study was conducted in two culturally different locations merely to account for the fact that cognitive biases may be modulated by culture, rather than to obtain an exhaustive description of these cultures per se. Moreover, we studied university students, which are often used as comparable subjects in cross-cultural studies; however, this setting, while allowing to test whether differences in bias-levels predict corresponding differences in WTP, does not allow for a generalization of willingness to engage in environmental action to the general population.

A second limitation pertains to the measurement of cognitive biases as they are referred to in the context of the hypothesis tested in this study. The hypothesis states that cognitive biases, as behavioral traits, that is, personality-specific cognitive dispositions, lead to counter-productive decision making in the context of climate-change challenges. Measuring cognitive biases as personality traits, defined as "an enduring personality characteristic that describes or determines an individual's behavior across a range of situations" (American Psychological Association, 2018c), can prove challenging as it can be argued that the testing situation itself provides context influencing the outcome. Nevertheless, standard psychological bias scoring methods try to be context neutral in the sense that they provide a context that refers equally to a wide range of situations. As such, one could argue that the standard methods used in our study could be further improved to provide better proxies for context independent dispositions. For example, it could be argued that while everybody "understands" money and lottery, psychological tests who use these tools may not elicit the desired perfectly cross-situational cognitive disposition, particularly as they manifest in a climate change decision-making context. Indeed, new scoring methods have been created recently that might be better suited, for example, a non-monetary assessment for loss aversion (Li et al., 2021). However, this eight item Likert scale questionnaire is not universally established yet. For example, Cabedo-Peris et al. (2024) found that in their study two question items had to be removed due to validity reasons. In addition to these contemplations on cognitive biases, one could argue that in those cases where cognitive biases in our study did not act as negative predictors, a reformulation of the bias to a more context specific, that is, environmental protection setting, might have resulted in a higher predictive value. As a reformulation of cognitive biases bears in itself a controversy about its validity, we felt that the first approach in the field to test the above hypothesis should be done with the respective standard methods. However, given our results, future studies should explore alternative cognitive definitions and measurements. For example, the Li et al. (2021) evaluation could possibly be adapted to a more environmental protection context. Although deviating from literal sense of the original hypothesis tested in this paper, investigating how climate change-specific biases predict environmental action could provide interesting insights. Such experiments would have to be designed in a way that they would not cause correlations simply due to similarities in measuring the dependent and independent variables, artificially creating a good match between the "bias/climate action willingness" axes, that could be interpreted as a self-fulfilling prophesy experimental design. However, such methods may prove valuable to detect mechanisms that have remained under the radar so far, and should therefore be a priority in future research.

A third potential limitation is that stated preferences may not always coincide with real behavior, as it can be influenced by hypothetical bias. However, in this study we are less interested in absolute WTP values, but rather in the relationship between cognitive biases and WTP, in order to test the claim of a negative relationship. We nevertheless followed best care practises designed at minimizing hypothetical bias and foster truthful preference revelation (Section 2.2.4 and Text S8 in Supporting Information S1) and enhance validity of value estimates (Section 2.3). This aspect was also part of our robustness check (Section 2.2.4 and Text S8 in Supporting Information S1). Additionally, when measuring prospect theory biases, previous literature has shown that using hypothetical scenarios and monies compared to using real-incentivized monies give similar results; suggesting survey methods and real-incentivized methods for measuring prospect theory biases are both suitable (Rieger et al., 2015, 2017; Ruggeri et al., 2020; Vieider et al., 2015).

Adding to these, it is possible that factors described in the literature (e.g., people's affinity to coasts, psychological distance of climate change, poverty) may have exerted confounding effects on WTP; however as stated above, our study does not focus on measuring absolute, real-life WTP values, but rather on changes in WTP relative to different bias levels (for a more extensive discussion see Text S15 in Supporting Information S1). Including these potential confounding variables in future studies, extending the studies to different demographic groups, and using more measures of mitigating behavior than WTP, would allow to better understand the influence of overall human behavioral factors on environmental action.

6. Conclusion

The claim that cognitive biases are substantial barriers to environmental action suggests one would expect to see a negative relationship between cognitive biases and people's desire to support climate mitigation as expressed in stated preferences. We find that the biases in general did not predict preferences for environmental action. Two exceptions exist: (a) loss aversion, which toward the extreme of the bias expression range, is a negative predictor in the German sample, and (b) positive illusion is a positive predictor in the Indonesian sample. In conclusion, cognitive biases may predict mitigation behavior; however, they do so only in a minority of cases, and where they do, the prediction does not necessarily have to be negative but can also be positive. These results suggest that the impacts, if any, of cognitive biases on environmental action are not uniform and cannot be deduced from theory in a straightforward way. These observations are in line with Atkinson and Jacquet (2021)'s critique against an overgeneralization of the impact that human psychological traits have on climate mitigation.

The observation that positive illusion is a significant positive predictor in the Indonesian student sample is promising as it: (a) contradicts a pessimistic narrative that biases act as severe barriers to climate change mitigation, and (b) even suggests that, in the right context, biases can promote environmental action. Our results also suggest that fostering the positive aspects of positive illusion, empowerment and a sense of control, could be promising tools for successful environmental policymaking. The observation that loss aversion is a negative predictor in the German student sample suggests that climate change awareness measures was not big enough to make the loss of future catastrophic consequences loom larger than the immediate loss of climate change measures. This does not mean that stressing the danger of future loss should not be an integral part of policymaking, but we argue that this strategy alone may not accomplish the goal. Therefore, combining the two strategies, fostering hope and empowerment while simultaneously continuing to emphasize the dangers of future climate-related catastrophes could provide a way forward for policymakers to establish effective climate policies. Positive goal settings like the UN SDGs and realistic positive small step visions toward an environmentally friendly future like the so-called Imagineering techniques are in line with such requirements.

Inclusion in Global Research Statement

This study was conducted as part of a Research Coordination Agreement between the Leibniz Centre for Tropical Marine Research (ZMT) Bremen and IPB University in Bogor Indonesia. We would like to thank IPB University for their partnership, support and use of resources during the field campaign.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Availability Statement

The quantitative and qualitative data used in the study are available at Archiving Basis GESIS—Leibniz Institute for the Social Sciences repository—via https://doi.org/10.7802/3030 with free access (see Moser et al., 2026a). R programming software (version 4.3.1) was used and is publicly available (R Core Team, 2023). The R scripts/code used to execute the analyses in the paper are preserved and freely accessible/available at Archiving Basis GESIS (see Moser et al., 2026b).

Acknowledgments
We acknowledge serval individuals who helped make this research possible, such as Peter Steiglechner, Lukas Tomberg, Muhamad Rizki, and Rifki Furquan for valuable input, Permata Mei Kartika for assistance in the Indonesian data collection, and the Bremen Research and Policy Lab (BreLAB) for assistance in the German data collection. This publication is part of the research project “Sea level change and the Tragedy of Cognition (SEATRAC)” (DFG project number: 423711127), which is part of the Priority Program (SPP-1889) “Regional Sea Level Change and Society (SeaLevel)” funded by the German Research Foundation. Open Access funding enabled and organized by Projekt DEAL.

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