Sustainability in Environment
ISSN 2470-637X (Print) ISSN 2470-6388 (Online)
Vol. 7, No. 1, 2022
www.scholink.org/ojs/index.php/se

*Original Paper*

# Response Efficacy in Environmental Discounting: Concern and Action towards Climate Change Threats

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Received: December 6, 2021    Accepted: December 12, 2021    Online Published: December 14, 2021

doi:10.22158/se.v7n1p7    URL: http://dx.doi.org/10.22158/se.v7n1p7

***Abstract***

*Extending preceding environmental discounting studies, we examined the role of response efficacy (in low, control, and high conditions) in participants' valuation of climate-change concern and action across four psychological distance dimensions (temporal, spatial, social, and probabilistic). Participants gave ratings of concern and action in the context of two hypothetical scenarios which were directly related to two different threats (droughts and floods) posed by unmitigated climate change. Rachlin's hyperboloid discount functions fit the data well. The previously observed gap between concern and action ratings was not replicated in the main analyses, but was seen in the ratings at the minimum distance values. Response efficacy differentially affected ratings of concern and action at the minimum distance values for the temporal, social, and probabilistic dimensions, but differentially affected discount values (k) only for the probabilistic dimension. Compared to their level of concern with the environmental threat, participants who were led to believe that their actions were not efficacious were less willing to engage in mitigation behaviors than participants who were led to believe that their actions were efficacious. The insights gained through the current research effort may be valuable for policymaking as well as intervention design aiming to increase societal mitigation and adaptation efforts.*

***Keywords***

*climate change, environmental concern, environmental discounting, pro-environmental behavior, response efficacy*

## 1. Introduction

The scientific consensus on climate change is clear: It is a global crisis. The Intergovernmental Panel on Climate Change (IPCC, 2018) stressed that individual behavioral changes are key in restricting the rise in global temperature. It is important to understand the factors that prevent people acting sustainably so that these barriers can be eradicated. Especially problematic is that the consequences of climate change are complex, somewhat uncertain, for the most part still in the future, and geographically as well as socially distant (Böhm & Tanner, 2019). Such psychological distance can lead to discounting.

Discounting describes the phenomenon whereby the subjective value of an outcome diminishes as the outcome becomes increasingly uncertain (Sargisson & Schöner, 2020), or temporally (Madden & Bickel 2010; McKerchar & Renda, 2012; Sargisson et al., 2021), socially (Kaplan et al., 2014), or spatially distant (Sargisson & Schöner, 2020). Discounting is among the numerous "dragons of inaction" or psychological barriers preventing people from acting towards climate-change mitigation (Gifford, 2011).

When outcomes are delayed in time, people discount their value. While temporal discounting has been found repeatedly for monetary outcomes, temporal considerations also play an important part in environmental decisions (Hardisty et al., 2012) and temporal discounting effects have been found in the contexts of soil and water pollution (Kaplan et al., 2014; Sargisson & Schöner, 2020), water (Viscusi et al., 2008) and air quality (e.g., Berry, Friedel et al., 2017; Berry, Nickerson, et al., 2017; Hardisty & Weber, 2009), environmental restoration (Meyer, 2013), and the storage of nuclear and hazardous waste (e.g., Moser et al., 2013).

Most environmental discounting studies have used relatively short timeframes (Kaplan et al., 2014; e.g., up to 25 years, Berry, Friedel, et al., 2017; McKerchar et al., 2019) not well suited for the prediction of behavior at extended delays or for the design of environmental policies (Berry, Nickerson, et al., 2017). Although a few researchers have investigated temporal discounting of environmental outcomes with longer delays (e.g., Berry, Nickerson, et al., 2017; Sargisson et al., 2021; Sargisson & Schöner, 2020), more studies directly investigating climate-change scenarios with long delays are needed.

When people perceive environmental problems to be worse in distant places (Gifford et al., 2009), their feeling of responsibility diminishes (Uzzell, 2000). For example, as distance increases, willingness to spend money on environmental improvements plummets (Hanley et al., 2003; Pate & Loomis, 1997) while support for planned coal and nuclear power plants rises (Hannon, 1994). People who do not visit specific environments devalue their quality significantly faster than visitors do (Viscusi et al., 2008). Generally, the farther away people are from an environment and its inhabitants the less concerned they are about its condition.

Sargisson and Schöner (2020) showed that people discount environmental outcomes as the spatial distance to the origin of the pollution increases. Similarly, Sparkman et al. (2021) found that if an environmental policy is only intended to benefit inhabitants of other countries, local people's support for that policy drops suddenly. Regarding climate change, spatial distance is especially relevant because the nations most affected by the consequences of climate change are often geographically separated from the nations causing it (see Ware & Kramer, 2019).

Social distance also affects discounting decisions (Jones & Rachlin, 2006; Rachlin & Jones, 2008) including decisions concerning environmental dilemmas (He et al., 2017; Vlek & Keren, 1992). Outcomes affecting people with whom one has formed stronger social bonds (e.g., friends) are given more consideration than outcomes affecting people with whom one has little to no social bond (e.g., a mere acquaintance), for example, people are more willing to intervene to help a victim of cyberbullying if the victim is socially closer to them (Hayashi & Tahmasbi, 2020). However intuitive this connection might seem, research in social discounting from any discipline is sparse (Gattig & Hendrickx, 2007), likely due to the fact that social relationships are difficult to contextualize for research applications, as a variety of factors such as people's nationalities, ages, and socioeconomic statuses have to be considered (Gattig, 2002). Jones and Rachlin (2006) described a simpler, more quantifiable method to investigate social discounting which entails asking participants to create an imaginary list of 100 people ranked by their social proximity. This method was effectively adapted by Kaplan et al. (2014) who found that an increase in social distance led to increased devaluation of environmental risks.

Gifford (2011) theorized that indications of uncertainty concerning climate change might be used to rationalize present and future inaction towards climate-change mitigation. Phrases indicating uncertainty with regard to climate-change mitigation and adaptation options within IPCC reports give rise to misinterpretations by laypersons (Budescu et al., 2009).

Uncertainty about environmental issues furthermore directly affects people's behavior. A reduction in the frequency of eco-friendly behavior at the individual and group level has been shown in resource dilemmas, where environmental outcomes are known or perceived to be uncertain (Hine & Gifford, 1996). Discounting researchers have found that as the probability of negative environmental outcomes decreases, the value of air (McKerchar et al., 2019), soil, and groundwater quality (Kaplan et al., 2014; Sargisson & Schöner, 2020) is increasingly discounted.

In contrast with the field of economics, in which discounting is typically modelled using a time-consistent, exponential model, in psychology, discounting rates are most frequently modelled using Mazur's (1987) time-inconsistent hyperbolic function. However, Rachlin's (2006) extended hyperboloid function has been found to be a better fit than Mazur's model. Rachlin's hyperboloid function is:

$$V = \frac{A}{1+kX^s} . \qquad \text{Equation 1}$$

$V$ is the participants' subjective rating of the outcome (e.g., the rating of climate-change concern and action). $X$ represents the psychological distance values, $s$ represents sensitivity of individuals to differences in the size of the outcome, and $k$ and $A$ are the slope and intercept of the function. The slope reflects the rate at which the outcome is discounted over increasing psychological distance, and the intercept the subjective value of the outcome at a distance value of zero. The intercept is usually a constant representing the maximum value of the outcome rating (100 in our study).

Sadly, people's environmental concern does not readily translate into pro-environmental behavior

(Gifford, 2011; Hornsey et al., 2016; Kollmuss & Agyeman, 2002; Sargisson & McLean, 2015). Two meta-analyses investigating the determinants of pro-environmental behavior reported a weak correlation between awareness of environmental problems and pro-environmental behavior (Bamberg & Möser, 2007; Klöckner, 2013). Not surprisingly, discounting studies concerning environmental outcomes reveal a similar concern-behavior gap (Kaplan et al., 2014; Sargisson & Schöner, 2020).

Several possible psychological barriers that keep people from acting pro-environmentally are known (Gifford, 2011) and judgmental discounting itself is one. However, other possible factors warrant investigation in discounting research. One factor that could keep individuals from acting to mitigate climate change, even though they are concerned, is a perceived lack of response efficacy - the degree to which an individual believes that their actions are truly effective. If people are concerned about climate change but perceive their actions to have little impact, they are less likely to report that they will act to mitigate climate change (Williams & Jaftha, 2020) and are also likely to show aversive reactions such as threat attenuation (O'Neill & Nicholson-Cole, 2009) and inaction (Gifford, 2011).

Increasing people's perceived response efficacy can heighten their intentions to perform mitigation (Jugert et al., 2016) and pro-environmental political behaviors (Geiger et al., 2017; Hart & Feldman, 2016), and public-sphere climate actions such as volunteering (Doherty & Webler, 2016). Therefore, by heightening the perception of response efficacy such that people believe that their actions will have an impact, it might be possible to close, or at least reduce, the concern-behavior gap seen in discounting tasks.

We studied ratings of concern about the consequences of climate change and willingness to act to mitigate climate change across values of four dimensions (temporal, spatial, social, and probabilistic).

Additionally, we manipulated perceived response efficacy (in low, high, and control conditions) concerning climate-change action in relation to two hypothetical but realistic scenarios highlighting different consequences of climate change. We used two different scenarios – one describing a flood and the other a drought – because these scenarios had not previously been tested and we wanted to be sure that at least one of these scenarios would be relevant to our participants.

We had three hypotheses. Hypothesis 1: Ratings of willingness to act and concern in relation to environmental outcomes are best described by a hyperbolic/hyperboloid model of discounting across temporal, probability, spatial, and social discounting tasks. Hypothesis 2: Ratings of willingness to act are discounted more steeply than ratings of concern in relation to environmental outcomes across temporal, probability, spatial, and social discounting tasks. Hypothesis 3: Ratings of willingness to act and concern in relation to environmental outcomes are discounted more similarly when perceived response efficacy is high rather than low across temporal, probability, spatial, and social discounting tasks.

## 2. Method

### *2.1 Participants*

We recruited 164 participants from the participant pool of the University of Groningen (about 500 first-year psychology students at the time) who received course credits for their participation. Additionally, 76 of the 596 second-year psychology students invited by email took part voluntarily. All participants were over 18 years and proficient in English. Of the 304 participants recruited, we excluded 49 because they did not complete the discounting tasks. We excluded an additional 15 participants either because they gave similar ratings, such as 0s or 100s, in the majority of discounting tasks or because their $k$ values were unrealistically high ($k$ values of 25 and above). We had intended (see our pre-registration; https://osf.io/nfzev) to winsorize outliers by changing them to 3SDs above (or below) the mean. As these high $k$ values were extremely large, the mean and SD were severely skewed, and did not accurately reflect the discounting that we observed because the unrealistically high $k$ values in our data occurred when rating values across all dimension values were equal or where ratings increased, rather than decreased, across increasing values of the dimension, and therefore large, positive $k$ values, suggesting high rates of discounting, did not represent the pattern of discounting reported by the participants. Therefore, we removed the participants rather than adjusting their data.

The final sample was 240 participants (aged from 18 to 31 years, $M$ = 20.4 years, $SD$ = 2.1 years), 76.3% women, mostly from European countries (93.8%), with the majority from Germany (40.4%) or the Netherlands (32.9%). No one indicated having neither a male nor a female identity.

The intended sample size was 250 because the a priori power analysis indicated that at least 246 participants would be needed for a between-subjects ANOVA with three groups, a small-to-medium effect size ($f$ = .2), power of 80%, and an alpha of .05. The sample did not differ in known ways from the target population and closely resembled the samples used by Kaplan et al. (2014) and Sargisson and Schöner (2020).

### *2.2 Procedure*

Prior to data collection, the Ethics Committee of Psychology (ECP) of the University of Groningen approved the research. We preregistered all relevant study information with the Open Science Framework (OSF) before collecting data (https://osf.io/nfzev).

Participants completed the questionnaire online, in English, at a time and place of their choice, within Qualtrics (https://www.qualtrics.com/). There was no time limit and participants could take a break. Median completion time was about 10 minutes.

After giving informed consent, participants provided their age, gender, educational level, and nationality. Next, participants completed the discounting tasks. Each participant completed discounting tasks for two scenarios presented in random order. One scenario described an outcome related to drought and the other to flooding. Before the scenario changed, participants were notified, so that they would pay attention to the text describing the new scenario. Participants were randomly assigned to one of three response-efficacy conditions (low/control/high).

For each scenario, each participant completed four discounting dimensions in a random order; the distance values for each dimension were also presented in a random order. All randomization was done automatically within Qualtrics and only the random assignment to condition was arranged so that group sizes would be approximately equal for the three conditions ($n_{\text{Low}}$ = 78, $n_{\text{Control}}$ = 82, $n_{\text{High}}$ = 80).

2.2.1 Temporal Discounting

Depending on the scenario, one of two task descriptions was presented in the discounting task for the temporal dimension. The distance values (1, 5, 10, 20, 50, and 100 years) were displayed in a random order to participants in each scenario.

Drought scenario: *Global temperatures could rise further due to human-caused climate change if no action is taken. Increased temperatures would lead to shrinking harvests for local farmers because of droughts. Upcoming food shortages might put you at risk in X years.*

Flooding scenario: *Global sea levels could rise further due to human-caused climate change if no action is taken. Heightened sea levels would lead to higher risks of flooding of local shorelines. Upcoming floods might put you at risk in X years.*

2.2.2 Spatial Discounting

Depending on the scenario, one of two task descriptions was presented for the spatial dimension. The distance values (10, 50, 200, 500, 1000, and 5000 kms) were displayed in a random order to participants in each scenario.

Drought scenario: *Global temperatures could rise further due to human-caused climate change if no action is taken. Increased temperatures would lead to shrinking harvests for farmers X km away because of droughts. Upcoming food shortages might put you at risk.*

Flooding scenario: *Global sea levels could rise further due to human-caused climate change if no action is taken. Heightened sea levels would lead to higher risks of flooding X km away. Upcoming floods might put you at risk.*

2.2.3 Social Discounting

Depending on the scenario, one of two task descriptions was used in the discounting tasks of the social dimension. The distance values (Person Number 1, 5, 10, 20, 50, and 100) were displayed in a random order to participants in each scenario. To prepare participants for the social discounting tasks, the following message was displayed before the participants read either of the discounting scenarios:

*Some of the following questions ask you to imagine that you have made a list of 100 people ranging from your closest friend or relative at position #1 to a mere acquaintance at #100. You do not have to physically create the list-just imagine that you have done so.*

Drought scenario: *Global temperatures could rise further due to human-caused climate change if no action is taken. Increased temperatures would lead to shrinking harvests for local farmers because of droughts. Upcoming food shortages might put person X on your list at risk.*

Flooding scenario: *Global sea levels could rise further due to human-caused climate change if no action is taken. Heightened sea levels would lead to higher risks of flooding of local shorelines.*

*Upcoming floods might put person X on your list at risk.*

2.2.4 Probability Discounting

Depending on the scenario, one of two task descriptions was used in the discounting tasks of the probability dimension. The distance values (95, 90, 50, 30, 10, and 5%) were displayed in a random order to participants in each scenario.

Drought scenario: *Global temperatures could rise further due to human-caused climate change if no action is taken. Increased temperatures would lead to shrinking harvests for local farmers because of droughts. There is a X% chance that upcoming food shortages put you at risk.*

Flooding scenario: *Global sea levels could rise further due to human-caused climate change if no action is taken. Heightened sea levels would lead to higher risks of flooding of local shorelines. There is a X% chance that upcoming floods put you at risk.*

*2.3 Discounting Measures*

2.3.1 Climate-Change Concern

After each scenario at every psychological distance (temporal, spatial, social, and probability), we asked "How concerned are you about the effects of climate change on food shortages/floods? Shift the slider below to indicate how concerned you are." The slider could be moved between 0 ("Not concerned at all") to 100 ("Very concerned") from its default center position (50).

2.3.2 Climate-Change Action

After answering the question about concern, for every scenario and psychological distance, all participants saw the question "How likely are you to take action in regard to climate change?" Participants in the low-response-efficacy condition then saw the sentence "It is not likely that your action will have an impact". Participants in the high-response-efficacy condition saw the sentence "It is **likely** that your action will have an impact." The control-condition participants did not see a sentence after the climate-change-action question. Then all participants saw the statement "Shift the slider below to indicate how likely you are to take action." The slider could be moved between 0 ("Not likely at all") to 100 ("Extremely likely") from its default center position (50).

*2.4 Relatability, Realism, and Manipulation checks*

Lastly, participants responded to six items on 5-point scales. Four of the items were about the perceived relatability ("Please rate how relatable the scenarios were to you") and the perceived realism of each scenario ("Please rate how realistic the scenarios were to you"). The relatability and realism scores ranged from 1 ("Not relatable at all' and 'Not realistic at all") to 5 ("Extremely relatable" and "Extremely realistic"). The remaining two items, one per scenario, served as a manipulation check and asked the participants to rate "how likely [their] chosen actions would have had an impact in the given scenarios", with scores ranging from 1 ("Not likely at all") to 5 ("Extremely likely").

*2.5 Data Analysis*

As in previous research (Kaplan et al., 2014; McKerchar et al., 2019; Sargisson & Schöner, 2020), we expressed the probabilistic distance as the odds against the event's occurrence, using the formula O =

(1 - *p*)/*p*, where *p* indicates the percent chance and O indicates the odds against. The probability values of 95, 90, 50, 30, 10, and 5% became the odds against values .053, .111, 1, 2.33, 9, and 19.

We computed the participants' individual discount rates, *k* (Equation 1), from their subjective ratings of climate-change concern and action for each scenario and dimension with the Discounting Model Selector version 1.8.2 (http://www.smallnstats.com/).

We used SPSS 27 (https://www.ibm.com/analytics/spss-statistics-software) for all statistical analyses.

2.5.1 Confirmatory Analyses

We performed four mixed analyses of variance (ANOVA) (one for each discounting dimension; temporal, spatial, social, and probabilistic) with individual *k* values as the dependent variables. The independent variables were the rating type (concern/action; within-subjects), type of scenario (drought/flooding; within-subjects), and the level of response efficacy (low/control/high; between-subjects). As Box's test of equality of covariance matrices was significant for all ANOVA, we used Pillai's trace, which is robust when sample sizes are equal (Field, 2013). All other parametric assumptions were met for the ANOVA and all other analyses.

2.5.2 Exploratory Analyses

As an exploratory analysis, we repeated the four ANOVA to explore ratings of concern and action at the lowest psychological distance for each scenario. Given that ratings are related to *k* values, we applied a Bonferroni correction to the results of all ANOVA, such that a *p* value less than .025 was required to reach significance.

2.5.3 Scenario Relatability and Realism

We ran two *t* tests with perceived realism and relatability scores as dependent variables and the type of scenario (drought/flooding) as within-subjects independent variables.

2.5.4 Manipulation Check

We ran two independent-samples *t* tests with the participants' perceived response efficacy for each scenario as dependent variables and the level of response efficacy (low/high) as the independent between-subjects factor.

## 3. Result

The parameter values, $R^2$, and *k* values for the fits of Equation 1 to the median ratings of concern and action for each dimension are in Table 1. The positive *k* values in Table 1 indicate that climate-change concern and action ratings decreased as the temporal, spatial, social, and probabilistic distance increased. The $R^2$ values of the fits for both scenarios were generally high ($M_{\text{Drought}}$ = .950, 95% CI [.936, .964], $M_{\text{Flood}}$ = .869, 95% CI [.769, .969]). Median ratings of action were consistently higher across distance values in the high-efficacy conditions than in the low-efficacy conditions. Such a pattern suggests that participants discounted climate-change outcomes less when they were led to believe that their actions would be efficacious.

**Table 1. Parameter Values for Fits in Figures 1 and 2**

| | | | Drought Scenario | | | Flooding Scenario | | |
|---|---|---|---|---|---|---|---|---|
| Dimension | Condition | Rating Type | *k* | *s* | $R^2$ | *k* | *s* | $R^2$ |
| Temporal | Low | Concern | .100 | .491 | .969 | .077 | .594 | .963 |
| | | Action | .210 | .329 | .945 | .171 | .421 | .973 |
| | Control | Concern | .088 | .480 | .992 | .091 | .480 | .991 |
| | | Action | .101 | .477 | .988 | .096 | .479 | .997 |
| | High | Concern | .074 | .559 | .992 | .043 | .604 | .061 |
| | | Action | .096 | .458 | .995 | .096 | .458 | .995 |
| Spatial | Low | Concern | .157 | .195 | .939 | .109 | .235 | .787 |
| | | Action | .291 | .131 | .957 | .179 | .193 | .875 |
| | Control | Concern | .100 | .244 | .948 | .078 | .288 | .934 |
| | | Action | .122 | .221 | .925 | .107 | .252 | .926 |
| | High | Concern | .117 | .212 | .862 | .080 | .297 | .924 |
| | | Action | .133 | .176 | .867 | .114 | .229 | .889 |
| Social | Low | Concern | .043 | .604 | .961 | .037 | .592 | .956 |
| | | Action | .079 | .476 | .955 | .078 | .483 | .076 |
| | Control | Concern | .036 | .671 | .976 | .047 | .590 | .966 |
| | | Action | .054 | .575 | .952 | .052 | .619 | .955 |
| | High | Concern | .045 | .566 | .934 | .040 | .622 | .942 |
| | | Action | .035 | .591 | .969 | .049 | .556 | .952 |
| Probabilistic | Low | Concern | .030 | .496 | .975 | .266 | .438 | .951 |
| | | Action | .392 | .281 | .972 | .355 | .388 | .963 |
| | Control | Concern | .298 | .436 | .941 | .367 | .273 | .939 |
| | | Action | .321 | .382 | .901 | .413 | .242 | .952 |
| | High | Concern | .276 | .418 | .934 | .287 | .435 | .933 |
| | | Action | .249 | .394 | .959 | .268 | .407 | .948 |

For every discounting dimension, the discount rate for concern was shallower than for action, however, there was a significant main effect of rating type on *k* values only for the probabilistic dimension (Table 2).

**Table 2. Means, 95% CI, and Within-Subjects Effects of Rating Type on *k* Values**

| Dimension | Rating Type | Mean *k* | 95% CI | *F* | *df* | *p* | R | Power |
|---|---|---|---|---|---|---|---|---|
| Temporal | Concern | .248 | .182, .313 | 2.74 | 1, 236 | .10 | .18 | .38 |
| | Action | .323 | .190, .456 | | | | | |
| Spatial | Concern | .300 | .217, .383 | 0.59 | 1, 237 | .44 | .10 | .12 |
| | Action | .353 | .214, .492 | | | | | |
| Social | Concern | .170 | .118, .222 | 4.27 | 1, 237 | .04 | .13 | .54 |
| | Action | .220 | .165, .274 | | | | | |
| Probabilistic | Concern | .398 | .358, .439 | 7.47 | 1, 235 | .007 | .04 | .78 |
| | Action | .471 | .411, .531 | | | | | |

There was no significant main effect of response efficacy (low/control/high) on *k* values for any discounting dimension (Table 3).

**Table 3. Main Effect of Response Efficacy on *k* Values**

| Dimension | Condition | Mean *k* | 95% CI | *F* | *df* | *p* | *r* | Power |
|---|---|---|---|---|---|---|---|---|
| Temporal | Low | .374 | .207, .541 | 0.83 | 2, 236 | .44 | .08 | .19 |
| | Control | .237 | .075, .398 | | | | | |
| | High | .246 | .082, .410 | | | | | |
| Spatial | Low | .390 | .229, .552 | 1.35 | 2, 237 | .26 | .10 | .29 |
| | Control | .219 | .062, .377 | | | | | |
| | High | .370 | .211, .530 | | | | | |
| Social | Low | .185 | .101, .268 | 0.54 | 2, 237 | .58 | .07 | .14 |
| | Control | .171 | .089, .252 | | | | | |
| | High | .229 | .147, .312 | | | | | |
| Probabilistic | Low | .485 | .408, .561 | 1.46 | 2, 235 | .23 | .11 | .31 |
| | Control | .429 | .354, .505 | | | | | |
| | High | .391 | .315, .467 | | | | | |

As Table 4 shows, the interaction between response efficacy and rating type (concern vs. action) on *k* values was significant for the probabilistic discounting dimension. For the probabilistic dimension, *k* values for action were higher than for concern in the low-response-efficacy condition but lower than the *k* values for concern in the high-response-efficacy condition. Such an interaction signifies that participants' ratings of action reflected steeper discounting of climate-change outcomes than their ratings of concern in the low-response-efficacy condition but shallower discounting in the high-response-efficacy condition. This pattern was not evident for the other discounting dimensions.

**Table 4. Interaction Effects of Response-Efficacy Condition and Rating Type on *k* Values**

| Dimension | Condition | Rating Type | Mean *k* | 95% CI | *F* | *df* | *p* | *r* | Power |
|---|---|---|---|---|---|---|---|---|---|
| Temporal | Low | Concern | .265 | .150, .380 | 2.50 | 2, 236 | .08 | .14 | .50 |
| | | Action | .483 | .249, .718 | | | | | |
| | Control | Concern | .246 | .135, .358 | | | | | |
| | | Action | .227 | .000, .454 | | | | | |
| | High | Concern | .232 | .119, .345 | | | | | |
| | | Action | .260 | .030, .490 | | | | | |
| Spatial | Low | Concern | .426 | .280, .572 | 1.20 | 2, 237 | .30 | .10 | .26 |
| | | Action | .354 | .111, .597 | | | | | |
| | Control | Concern | .199 | .057, .342 | | | | | |
| | | Action | .240 | .003, .476 | | | | | |
| | High | Concern | .275 | .131, .419 | | | | | |
| | | Action | .465 | .225, .705 | | | | | |
| Social | Low | Concern | .133 | .042, .225 | 1.82 | 2, 237 | .17 | .12 | .38 |
| | | Action | .236 | .141, .331 | | | | | |
| | Control | Concern | .175 | .086, .264 | | | | | |
| | | Action | .166 | .074, .259 | | | | | |
| | High | Concern | .203 | .112, .293 | | | | | |
| | | Action | .256 | .162, .350 | | | | | |
| Probabilistic | Low | Concern | .380 | .309, .450 | 6.74 | 2, 235 | .001 | .23 | .92 |
| | | Action | .589 | .484, .694 | | | | | |
| | Control | Concern | .415 | .346, .484 | | | | | |
| | | Action | .444 | .341, .547 | | | | | |
| | High | Concern | .401 | .331, .471 | | | | | |
| | | Action | .381 | .277, .485 | | | | | |

There was no main effect of scenario type on $k$ values (all $p > .10$) for any of the four discounting dimensions.

We repeated the ANOVA for each dimension using individuals' ratings at the lowest psychological distance to explore effects on the initial value of the outcome rather than the rate of discounting of the outcome. Using ratings as the dependent variable, the initial rating for concern was higher than for action for every dimension (Table 5). Additionally, the interaction between response efficacy and rating type was significant for the temporal: $F(1, 237) = 4.76$, $p = .009$, $r = .20$; social: $F(1, 237) = 3.80$, $p = .024$; $r = .18$; and probabilistic dimensions: $F(2, 237) = 6.08$, $p = .003$, $r = .22$, but not for the spatial,

$F(1, 237) = 3.01$, $p = .051$, $r = .16$, dimension.

**Table 5. Means, 95% CI, and Within-Subjects Effects of Rating Type on Ratings at the Lowest Psychological Distance**

| Dimension | Rating Type | Mean rating | 95% CI | *F* | *df* | *p* | R | Power |
|---|---|---|---|---|---|---|---|---|
| Temporal | Concern | 86.98 | 85.03, 88.92 | 12.35 | 1, 237 | .001 | .22 | .94 |
| | Action | 84.12 | 82.08, 86.17 | | | | | |
| Spatial | Concern | 83.32 | 81.33, 85.32 | 12.87 | 1, 237 | <.001 | .23 | .95 |
| | Action | 80.38 | 78.29, 82.47 | | | | | |
| Social | Concern | 92.37 | 90.58, 94.16 | 14.07 | 1, 237 | <.001 | .24 | .96 |
| | Action | 89.63 | 87.65, 91.60 | | | | | |
| Probabilistic | Concern | 92.38 | 91.05, 93.71 | 28.46 | 1, 237 | <.001 | .33 | 1.00 |
| | Action | 88.57 | 86.90, 90.25 | | | | | |

Figure 1 shows that mean slopes of functions fitted to concern and action (left panel) were inconsistent, and the standard errors of the mean largely overlapped, except for the low-efficacy condition for the temporal and probabilistic dimensions where the slopes for action were steeper than for concern. A more consistent pattern is shown for the mean initial ratings (right panel). Whereas in control and high-efficacy conditions, mean ratings for action were only slightly lower than for concern, for the low-efficacy participants, mean ratings for action were considerably lower than those for concern.

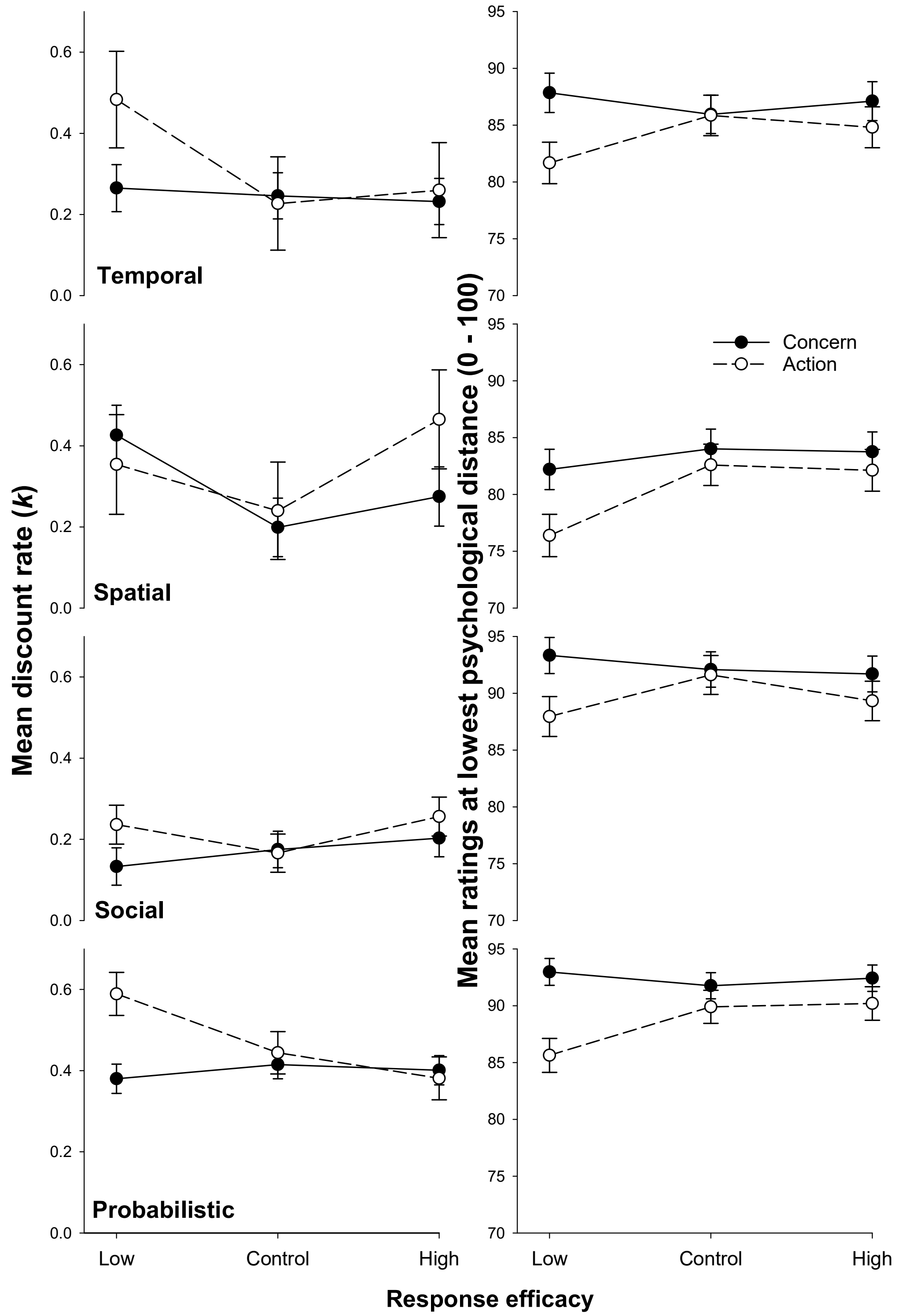


**Figure 1. Interactions Between Response Efficacy and Rating Type. The Left Panel Shows Mean *k* Values and the Right Panel Mean Ratings at the Lowest Value of each Dimension. The Rating Type (concern/action) Are Indicated by Solid (Filled Circles), Dashed (Empty Circles) Lines. Error Bars Show the Standard Error of the Mean**

Table 6 shows that participants perceived the flooding scenario to be significantly more relatable and more realistic than the drought scenario.

**Table 6. Scenario Relatability and Realism Results**

| | | Mean | 95% CI | *t* | *df* | *p* | *d* |
|---|---|---|---|---|---|---|---|
| Relatability | Drought | 2.37 | 2.23, 2.52 | -7.25 | 239 | <.001 | 1.26 |
| | Flood | 2.96 | 2.82, 3.11 | | | | |
| Realism | Drought | 3.03 | 2.88, 3.17 | -6.83 | 239 | <.001 | 1.12 |
| | Flood | 3.52 | 3.39, 3.66 | | | | |

Participants perceived their response efficacy to be significantly higher in the high-response-efficacy condition than in the low-response-efficacy condition for the drought scenario, but not for the flood scenario (Table 7).

**Table 7. Results of Manipulation Checks**

| Scenario | Efficacy | Mean | 95% CI | *t* | *df* | *p* | *d* |
|---|---|---|---|---|---|---|---|
| Drought | Low | 3.25 | 3.05, 3.45 | -2.68 | 156 | .008 | 1.01 |
| | High | 2.82 | 2.58, 3.06 | | | | |
| Flood | Low | 2.69 | 2.43, 2.95 | -1.63 | 156 | .10 | 1.09 |
| | High | 2.98 | 2.75, 3.20 | | | | |

## 4. Discussion

Our results supported Hypothesis 1. In line with previous research, temporal (e.g., Berry, Friedel, et al., 2017; Berry, Nickerson, et al., 2017; Hardisty & Weber, 2009; Kaplan et al., 2014; Meyer, 2013; Moser et al., 2013; Sargisson et al., 2021; Sargisson & Schöner, 2020; Viscusi et al., 2008), spatial (Hanley et al., 2003; Hannon, 1994; Pate & Loomis, 1997; Sargisson & Schöner, 2020), social (Kaplan et al. (2014), and probabilistic distances (Kaplan et al., 2014; McKerchar et al., 2019; Sargisson & Schöner, 2020) were important in the valuation of environmental outcomes. Participants prioritized psychologically close outcomes in the context of climate change. The discounting data for the four dimensions were well described by Rachlin's hyperboloid discounting function (Equation 1).

Contrary to Hypothesis 2, a significant difference in $k$ values for ratings of concern versus action was only found for the probabilistic dimension (Table 2). The expected discrepancy between concern and action present in previous environmental discounting research (Kaplan et al., 2014; Sargisson & Schöner, 2020) was not apparent in the results of the main analyses. However, in our exploratory analyses for all four dimensions, the initial ratings (at the lowest distance) of concern were higher than for action. A concern-behavior gap is apparent, then, at least at short psychological distances. Having lowered the initial rating of willingness to act relative to concern, it appears that ratings for both concern and action were then discounted at similar rates.

Hypothesis 3 was not supported. Using *k* values (discounting rate) as the dependent variable, the interaction between rating type (concern vs. action) and response efficacy was significant only for the probabilistic dimension. However, in the exploratory analyses, the same interactions using ratings at the lowest distance value were significant for three of the four dimensions. Ratings for action at the lowest distance values (Figure 1; right panel) were only slightly lower than the same ratings for concern for participants in the control and high-efficacy conditions but were substantially lower for participants in the low-efficacy conditions. Thus, there was a drop, at the shortest psychological distance, in the degree to which people stated they would act when they believed that their action would not be effective. This drop is analogous to a decrease in the intercept of the fitted function. Increasing perceived efficacy appears to have affected the degree to which participants were willing to act immediately to mitigate climate change, but not the rate of discounting over time. An increased willingness to act pro-environmentally by people who feel that their actions are effective is in line with previous research showing similar effects of response efficacy (e.g., Bradley et al., 2020; Doherty & Webler, 2016; Geiger et al., 2017; Hart & Feldman, 2016; Jugert et al., 2016).

Although participants' self-rated response-efficacy scores were higher in the high- compared to the low-response-efficacy condition for both scenarios, this difference was only significant for the drought scenario. We used a single sentence to manipulate response efficacy, therefore, upcoming research could investigate whether a stronger manipulation leads to more pronounced differences between concern and action ratings across discounting dimensions. Our findings nevertheless have practical implications. Interventions to increase pro-environmental behavior that target environmental concern, for example, need to ensure that their target population perceives their actions to be efficacious with respect to the threat causing the concern. This is especially true for environmental threats that are uncertain or temporally or socially distant. Furthermore, interventions using perceived response efficacy to increase climate-change mitigation behaviors should avoid messages highlighting spatially distant consequences. Researchers have found that support for environmental policies drops suddenly when the policies are beneficial only to people outside the participants' country of residence (Sparkman et al., 2021), thus, discounting of environmental outcomes over spatial distance may be more difficult to overcome than discounting in relation to other psychological distances. In our study, discounting across spatial distance was not as affected by heightened response efficacy as it was for the other dimensions. Future interventions would benefit from further research into the underlying causes of the concern-behavior gap.

Both Kaplan et al. (2014) and Sargisson and Schöner (2020) raised concerns about the extent to which their participants could relate to the hypothetical scenarios used in their studies. Our participants perceived the flooding scenario to be significantly more relatable and realistic than the drought scenario, which may be due to the fact that the participants resided in the Netherlands – a country at immediate risk of flooding. Remarkably though, no major differences in discounting judgments were revealed between the two different scenarios, indicating that even though hypothetical scenarios might be perceived as more or less relatable and realistic, researchers can have confidence in their discounting results, and can compare their results across studies with slightly different scenarios. Future research could investigate whether scenarios differ in respects that could affect discounting judgments. Moser et al. (2013), for example, found that participants' emotional involvement in the environmental outcome affected discounting behaviors.

Although our sample closely resembled samples in similar previous research (Kaplan et al., 2014; Sargisson & Schöner, 2020), the generalizability of the results is somewhat limited. Our sample was comprised of mainly young, educated women from Western Europe. Whereas education level is only a very weak positive predictor of altruistic and biospheric values in European samples, gender and age are stronger predictors (Sargisson et al., 2020). However, comparisons between populations with different demographics are rare in environmental discounting research. Although there are several studies showing differences in discounting decisions across time between people from different cultures in economics (e.g., Du et al., 2002; Ishii et al., 2017; Kim et al., 2012), cultural differences in the discounting of environmental outcomes have rarely been investigated. Where they have, discounting rate differences have been found. For example, Japanese participants are more likely to discount future air quality gains than American participants (Iwaki, 2011). Considering that climate-change mitigation and adaptation efforts require behavioral change from citizens around the globe, it would be worth investigating whether cultural and other demographic factors affect the discounting of climate-change concern and action.

Though we explored all four psychological distance dimensions (temporal, spatial, social, and probabilistic), participants rated their concern and action for only one dimension at a time. Because people are affected by all four dimensions concurrently, it would be worth examining how people rate environmental outcomes in scenarios that combine two or more dimensions (Gattig & Hendrickx, 2007). Especially important are the temporal and probabilistic dimensions because scientific reports aiming to inform policymakers about possible actions regarding climate-change threats usually refer to impacts over time (e.g., IPCC, 2018) and contain phrases communicating uncertainty (Budescu et al., 2009).

Overall, our study improved foregoing environmental discounting research by assessing its relevance to the pressing threat posed by climate change. The insights gained about the effect of varying psychological distances towards the consequences of climate change on human environmental decision-making, as well as the role of response efficacy may be valuable for policymaking as well as intervention design aiming to increase societal mitigation and adaptation efforts.

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