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Risky Therefore Not Beneficial: Replication and Extension of Finucane et al.'s (2000) Affect Heuristic Experiment

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Abstract

Risks and benefits are negatively related in people's minds. Finucane et al. causally demonstrated that increasing risks of a hazard leads people to judge its benefits as lower. Vice versa, increasing benefits leads people to judge its risks as lower (original: $r = -.74$ [-0.92, -0.30]). This finding is consistent with an affective explanation, and the negative relationship is often presented as evidence for an affect heuristic. In two well-powered studies, using a more stringent analytic strategy, we replicated the original finding. We observed a strong negative relationship between judgments of risks and benefits across three technologies, although we do find that there was no change in risks when highlighting low benefits. We note that risks seem to be more responsive to manipulation (as opposed to benefits) and find evidence that the negative relationship can depend on incidental mood. We provided materials, data sets, and analyses on https://osf.io/sufjn/.

Keywords

affect heuristic, judgment and decision-making, heuristics, risk, replication

Introduction

People tend to view risks and benefits as negatively related: the riskier something is, the less beneficial it is. However, risks and benefits are distinct concepts and are sometimes even positively correlated—some technologies or hazards that are beneficial may be high or low in risk, but those that are not beneficial are unlikely to be high in risk. In a seminal article, Finucane et al. (2000) proposed that the negative relationship occurs due to an *affect heuristic* (AH) whereby people rely on affect when judging the risks/benefits of specific hazards. Furthermore, they demonstrated evidence that is consistent with an affective explanation of this relationship. Take nuclear energy for example. The AH proposes that increasing the risks of nuclear energy (e.g., by exalting the hazard uranium has for human health) turns the affective evaluation associated with it negative, thereby leading people to judge its benefits as lower. Vice versa, increasing benefits leads to positive affect and to people judging its risks as lower (see Table 1).

Affect Heuristic

Affect is a crucial component of people's decision-making (Kahneman, 2003, 2011; Lerner et al., 2015; Loewenstein et al., 2001; Rachlin, 2003). It is argued that reliance on affect is often a much quicker, easier, and more efficient way to navigate the complexities of everyday decision-making (Damasio, 1994; Schwarz & Clore, 1983) and that affect informs many judgments and decisions (Albarracín & Kumkale, 2003; Peters et al., 2006; Schwarz, 2012; Slovic et al., 2002; Wyer et al., 1999).

Early studies of risk perception have shown that feelings of dread are major determinants of public perception and acceptance of risk for a wide range of hazards (Slovic, 1987). Focusing on this link, Finucane et al. (2000) proposed that people use an *affect heuristic* (AH) when making risk judgments. According to this view, people may use their affective response to a risk (e.g., "How do I feel about nuclear energy?") to infer how large they consider the risk to be. The argument is that: "Using an overall, readily available affective impression can be far easier—more

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Table 1. Summary of the Predictions According to the Affect Heuristic (AH).

Manipulated attribute	Impact on affect	Impact on non-manipulated attribute
Risk is high	Negative affect	Benefit is low
Risk is low	Positive affect	Benefit is high
Benefit is high	Positive affect	Risk is low
Benefit is low	Negative affect	Risk is high

efficient—than weighing the pros and cons or retrieving from memory many relevant examples, especially when the required judgment or decision is complex or mental resources are limited" (Finucane et al., 2000, p. 3).

Reliance on affect is a general process and, consistent with an AH, a wide range of findings support the idea that affect provides valuable information that people use to simplify their decision-making. For instance, affect-laden imagery has been shown to predict people's preferences in investment decisions (MacGregor et al., 2000), smoking (Benthin et al., 1995), information integration (Anderson, 1981; Efendić et al., 2019), simple choice gambles (Bateman et al., 2007), and morality judgments (Slovic & Västfjäll, 2010).

Risks and Benefits

For a long time, the negative relationship between judgments of risks and benefits puzzled researchers (Fischhoff et al., 1978) as these judgments should be positively correlated or independent of one another (Slovic, 1987). In a breakthrough study, Alhakami and Slovic (1994) found that the negative relationship was linked to how a person generally feels about a hazard. Later, Finucane et al. (2000) showed that the inverse relationship between risk and benefits was strengthened under time pressure designed to limit analytic thinking (their Study 1) and that it is causally determined. Specifically, manipulating one attribute—for example, increasing risk—led to an affectively congruent but inverse relationship, that is, decreased benefit and vice versa (their Study 2).

This inverse relationship has been observed elsewhere as well. It has been found that when general negative affect is evoked (i.e., participants were shown photographs depicting houses in flooded regions), this led to increased levels of perceived risk (Keller et al., 2006). Similarly, incidental negative affect (e.g., negative mood) was found to amplify reliance on affect, which led to stronger negative correlations between risks and benefits (Västfjäll et al., 2014). Interestingly, affective association with a particular hazard has been shown to influence the interpretation of new information. People evaluated nuclear power more negatively than solar power because of more negative feelings associated with nuclear power (Siegrist & Sütterlin, 2014). Similar negative associations between risk and benefits have been found in consumer judgments of novel products (King & Slovic, 2014), in the financial domain (Ganzach, 2000), and in wood smoke pollution (Bhullar et al., 2014). Recently, Skagerlund et al. (2020) found that the negative correlation is tied to cognitive reflection ability.

Replication Value and Present Research

In this article, with two well-powered studies, we aimed to closely replicate and extend our understanding of the causal demonstration of the negative relationship between risks and benefits, using the same materials and procedure as in the original paper (Finucane et al., 2000).

We chose to replicate Study 2 from Finucane et al. (2000) for several reasons. First, while many correlational studies have found the negative relationship, few demonstrated it causally. King and Slovic (2014) used a similar method as Finucane and colleagues, but other work mostly found correlational support (some research has even failed to find the same relationship, Raue et al., 2019). There is therefore value in demonstrating, with sufficient statistical power, whether the causal effect is robust. Second, the analysis approach used in the original studies and in later demonstrations of the negative relationship (e.g., King & Slovic, 2014) were nonstandard, failing to account for non-independence of data and relying on counting the number of times the manipulation worked in the predicted direction—a strategy that leads to large information loss. A more stringent analytic approach with mixed-effect modeling ought to provide information on the generalizability of the effect. Third, the findings are relevant for risk communication. Changing risk/benefit judgments by manipulating solely one attribute (either risk or benefit) has vast applied potential. Risk campaigns can focus on changing people's judgments about many plights of today's society (e.g., smoking, obesity, and so on). Fourth, as of this writing, we are unaware of any other attempts to directly replicate this study. This is surprising given the relevance in understanding the relationship between risks and benefits, as well as the popularity of the original article and how it promoted the AH in the judgment and decision-making literature. As of this writing, the original article has been cited 3,363 times with a later updated review article being cited 3,860 times (Slovic et al., 2007).

We also wish to highlight an important distinction. The observation of the negative relationship is often presented as evidence for an AH in risk judgments. For example, observing the negative relationship leads authors to conclude that the AH is a robust phenomenon (Skagerlund et al., 2020). However, the original, as well as many other studies, fail to demonstrate that it is affect that mediates this relationship (although converging evidence on the importance of affect would suggest this is the case). Our aim here is to replicate the negative causal relationship between risks and benefits. As such, this replication also does not speak to the mechanism that underlies the relationship. Other more cognitive, rather than affective, mechanisms remain a plausible explanation. Nevertheless, we hope that investigating whether the causal relationship replicates will (a) provide important insight into this interesting phenomenon and (b) serve other researchers who wish to use the paradigm to further understand whether it is affect or something else that explains it.

We thus consider this investigation to be a needed direct replication. Replications should be sufficiently similar to the original study to adequately gauge support for the original findings (LeBel et al., 2019). Furthermore, given the prevalence of publication bias (Bakker et al., 2012), a close replication adds value by providing evidence that strengthens or weakens the finding.

Overview of Studies

This replication was part of an ongoing replications project (see Supplementary Figure S1 and the project process section in the supplementary material for more details). We crowdsourced the replication using two teams, both teams being supervised by experienced authors. Each team collected data independently and wrote detailed preregistrations. We thus report the results of two studies serving as close replications of Study 2 from Finucane et al. (2000), using the same methodology and the same materials.[1] The two studies differ only in the target sample, one obtained on MTurk (U.S. participants) and the other on Prolific (U.K. participants). The two studies were preregistered on the OSF (MTurk: https://osf.io/ab5dw/files/; Prolific: https://osf.io/p4qjx/files/).[2] All materials, data sets, and analysis scripts are available on OSF (https://osf.io/sufjn/). We report how we determined the sample size, all data exclusions (if any), all manipulations, and all measures.

Extensions

In addition to the direct replication of Study 2 from Finucane et al. (2000), we also report two extensions. First, we looked at the effect of naturally occurring incidental mood on the negative relationship between judgments of risks and benefits. In the MTurk sample, participants were asked to rate their current levels of (a) pleasure—*unpleasant* vs. *pleasant* and (b) arousal—*deactivated* vs. *activated* (using two affective sliders that ranged from −100 to 100, centered in the middle). We based our measure on core affect that represents states experienced as simply feeling good or bad, energized, or enervated (Russell, 2003). We use the term "naturally occurring incidental mood" to highlight that this is a measured rather than manipulated variable and that the affect in question is incidental (i.e., unrelated to the judgment at hand). Any affect that arises due to changes in risk/benefit descriptions is integral (i.e., affect stemming from the judgment target at hand). Several predictions can be made on how naturally occurring incidental mood could impact the negative relationship: (a) incidental mood is misattributed (Schwarz, 2012) to risk/benefit judgments impacting the strength of the negative correlations, (b) incidental affect has a specific effect in that negative incidental affect leads to high risk and low benefit, while positive incidental affect leads to low risk and high benefit, not impacting the strength of the negative correlations; or (c) it has a negation effect where, akin to mood regulation models for example (Andrade, 2005), being in a pleasurable naturally occurring mood may interfere with people's ability to effectively map a negative change in integral affect (e.g., by describing risks as high). Highlighting the interaction between such incidental and integral states can offer insights into the role of affect in the negative relationship.

Second, we explored whether there was a stronger negative relationship when risks, as opposed to benefits, are manipulated. Illuminating this boundary condition could provide insight into which of these two attributes people find more informative or important for their risk judgments.

Method

Participants

In the first study, a total of 806 participants from the United States were recruited through MTurk using the TurkPrime platform (Litman et al., 2017). In the second, a total of 1,008 participants from the United Kingdom were recruited through Prolific. To determine the number of participants needed, we conducted a power analysis planning to detect the weakest effect size reported in the original *that was also significant* (at $p < .05$). Therefore, given our resource constraints, we based our power analysis on having 95% power to detect a Cohen's $d_z = 0.30$. This resulted in a suggested sample size of 147 participants per condition and a total of 588 across 4 between-subject conditions. Finally, we aimed for a higher sample size between 750 and 800 participants, as this would also ensure we were able to detect a smaller effect size (Cohen's d_z) of .20 at 80% power. A comparison of the target article sample and the replication samples is provided in Table S1 in the supplementary material.

To obtain the final sample, we first excluded (30 from MTurk sample and 40 from Prolific sample) participants following our preregistered exclusion criteria.[3] Because the studies were identical, we combined[4] them for the final data analysis, resulting in 1,552 participants (*MTurk* = 776; *Prolific* = 776; M_{Age} = 38.99, SD_{Age} = 12.30; 822 females, 727 males, 3 would rather not say).

Design, Procedure, and Measures

Both studies had a 2 (Between-subject factor—Direction: High vs. Low) × 2 (Between-subject factor—Manipulated Attribute: Risk vs. Benefit) × 3 (Within-subject factor—Technology Scenario: Nuclear Power vs. Natural Gas vs. Food Preservative) mixed-subject design (see Table S3 and Table S4 in the supplementary material for more details and full descriptions of the measures and direction/attribute information). Please note that the second study (Prolific) included an additional experimental condition that was excluded due to a methodological issue.[5]

Participants were first asked to answer questions regarding the perceived benefit and risk of all three technologies (Nuclear Power, Natural Gas, Food Preservatives)—the same ones used in the original study. The presentation of the technologies was randomized. Participants were asked two questions, in random order, for each technology, namely: "In general, how risky [beneficial] do you consider the use of nuclear power / natural gas / food preservatives?"[6], answering on a 10-point scale from 1 (*not at all risky [beneficial]*) to 5 (*moderate risk [benefit]*) to 10 (*very risky [beneficial]*).

Subsequently, dependent on the conditions, participants were presented with textual vignettes designed to change the affective quality (e.g., high risk = negative, high benefit = positive, and so on) of the scenarios. We used the same descriptions from the original study (https://osf.io/y97tp/). For example, in the low benefit condition for the hazard natural gas, participants were presented with the following text (shortened):

> Natural gas is used as a source of energy in the US. Natural gas has the property of being a gas at room temperature, which allows it to be burned to produce heat. However, this same gaseous property limits the energy tasks that natural gas can be used for. Natural gas is not able to replace electricity for such tasks as lighting, or the numerous jobs that need electric motors, such as refrigeration or the operation of machinery.

After reading the information, participants again provided answers to the risk and benefit questions for each technology scenario. Please note that once participants were assigned to one of the between-subject conditions, they were in that condition for all three scenarios, as the scenario was a within-subject variable. This means that we had data from 4,656 trials. Finally, participants answered a funneling section and provided demographic information. At the end of the study, a short debriefing was given regarding the study's purpose and confidentiality. We characterize the current replication as a "very close replication" based on the framework for classification of the replications using the criteria by LeBel et al. (2018; see Table S45 in the supplementary material).

Results

Analysis Strategy

We report both the original (i.e., repeating the same analytic strategy as in Finucane et al., 2000) and an improved analytic approach. For the improved, we employed linear mixed-effects models (LMEM) using the lme4 package in *R* (Bates et al., 2015). Significance for fixed effects was assessed via Satterthwaite's degrees of freedom (Kuznetsova et al., 2017). Unless stated otherwise, the models adjusted for covariates at Level 1 (ratings of risks and benefits before the experimental treatment) and Level 2 (i.e., Technology type and participants' ID were treated as random effects). We added pre-scores on the manipulated/nonmanipulated attribute to reduce noise of our assessment and to check whether the preratings may moderate the effect of the manipulation. LMEMs reduce the chance of Type I errors, account for nonindependence of data points (e.g., within-subject observations), provide a greater flexibility with specification of the covariance structure, and allow us to make more generalizable claims across samples of participants and stimuli (hazards in our case; Judd et al., 2012).

Original Data Analytic Approach (Finucane et al., 2000)

Descriptive statistics of the measures across the two samples are noted in Table S39 and Table S40 of the supplementary material. Following the original approach, we conducted paired samples t tests (two-tailed). Specifically, for each technology, we compared the mean pre- and post-manipulation ratings of the manipulated and the non-manipulated attributes. Positive t-values indicate that there was an increase in rating after manipulation. Negative t-values indicate there was a decrease in rating after manipulation. The results are in line with the original finding (See Table S41–S44 in the supplementary material for the detailed results). That is, for the manipulated attribute ratings, providing information on high and low benefits or risks led to higher and lower post-manipulation ratings of benefits or risks. For the non-manipulated attribute, we see the inverse: providing information on high and low benefits or risks led to lower and higher post-manipulation ratings of risk and benefits.

Furthermore, we tested the correlation between risk and benefits using the t-values from the abovementioned analysis. We found strong support for a negative correlation: MTurk sample: $r(10) = -.87$, 95% confidence

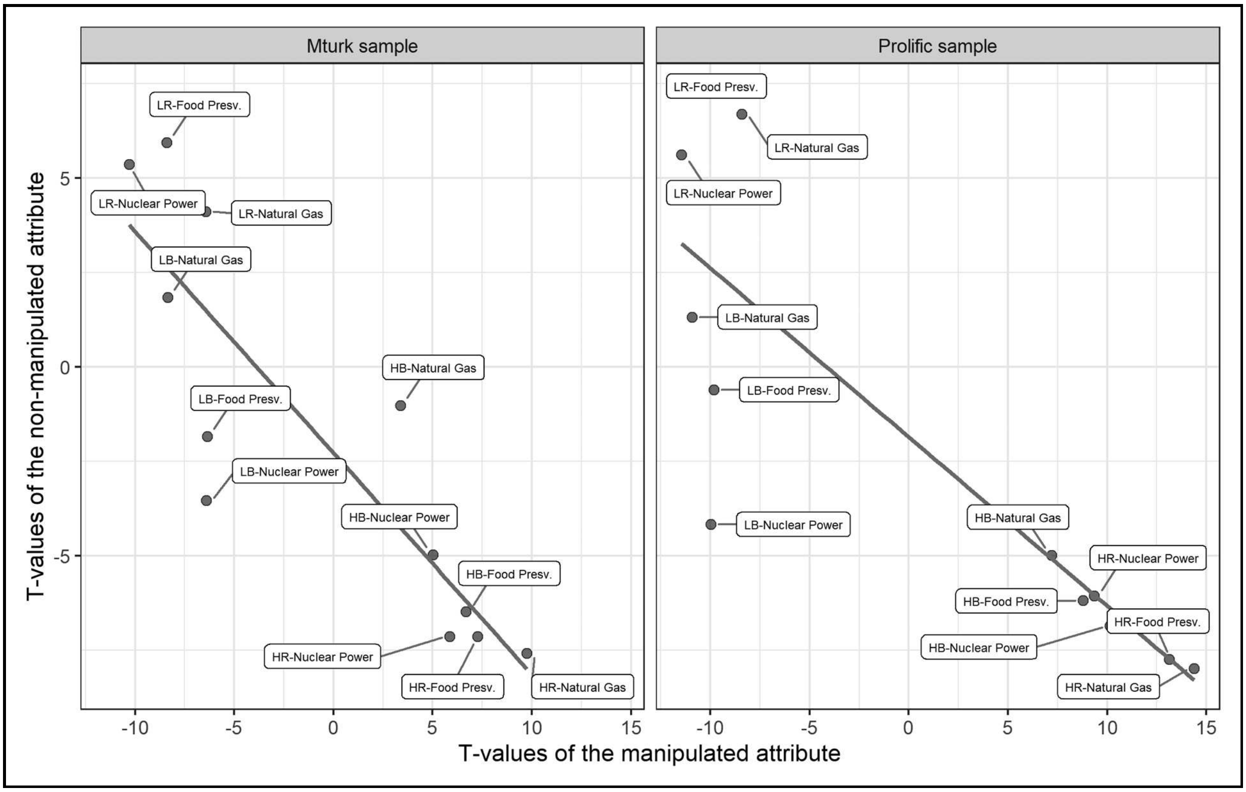

Figure 1. t-Values for Manipulated Versus Non-Manipulated Attributes.
Note. t-values for four-direction/attribute information manipulations (HB = High Benefit; LB = Low Benefit, HR = High Risk, LR = Low Risk) for the three technologies (nuclear power, natural gas, and food preservatives) across the two samples (MTurk and Prolific). The negative slope shows the predicted negative relationship between risks and benefits—as benefits increase risks decrease and as risks increase benefits decrease.

interval (CI): [−0.96, −0.59], $p = .003$; Prolific sample: $r(10) = -.84$, 95% CI = [−0.95, −0.50], $p < .001$. Plotting the *t*-values in Figure 1, the negative slope shows that when ratings on the manipulated attribute increase, ratings on the non-manipulated attribute decrease (and vice versa). Simply put, when benefits increase risks decrease and when risks increase benefits decrease, indicating a negative relationship.

Mixed-Model Approach

Manipulation Checks. We conducted LMEMs with change in the manipulated attribute as the DV (i.e., ratings on a manipulated attribute after experimental treatment minus ratings on manipulated attribute before experimental treatment; 0, therefore indicates no change, a positive value an increase, and negative value indicates a decrease). Table 2 presents the fixed-effects coefficients with all the predictors (See Table S11–S14 in the supplementary material for step-by-step regression results).

The significant effect of Direction shows that, regardless of the manipulated attribute, if the direction was high there was a positive change while if the direction was low there was a negative change, indicating a successful manipulation check (see Figure 2 and Tables S41–S44 for detailed statistics).

Negative Relationship Between Risks and Benefits. To test whether we observe a negative relationship between risks and benefits, we looked at the effects of the manipulated attribute on the nonmanipulated attribute. Specifically, we regressed change in ratings of nonmanipulated attributes (DV) on Direction, Manipulated Attribute, and their interaction, adjusting for covariates at Level 1 (Pre-rating manipulated attribute; and three-way interaction between pre-rating non-manipulated attribute, Direction, and Manipulated Attribute) and Level 2 (i.e., Technology type and participant's ID). Table 3 summarizes these results (see Table S20–S24 in the supplementary material for step-by-step regression results and model comparisons).

The main effect of direction supports the original finding of the negative relationship. In addition, we find that the directionality of pre- and post-treatment changes in the non-manipulated attribute was consistent with the predicted inverse relationship, except in the Low-benefit condition (see Figure 3 and Tables S41–S44 for detailed statistics).

Table 2. Estimated Fixed-Effects Coefficients of the Mixed-Effects Regression Model With Change in the Manipulated Attribute as the DV.

Predictors	DV: Change in non-manipulated attribute			
	B	*SE*	95% CI	*p*
Intercept	−0.09	0.06	[−0.21, 0.04]	.185
Pre-rating manipulated attribute (PMA)	−1.09	0.03	[−1.15, −1.03]	**<.001**
Direction (high vs. low)	2.56	0.07	[2.42, 2.69]	**<.001**
Manipulated attribute (risk vs. benefit)	−0.27	0.07	[−0.40, −0.13]	**<.001**
Direction × manipulated attribute	0.49	0.14	[0.22, 0.75]	**<.001**
PMA ×direction	−0.10	0.06	[−0.22, 0.02]	.109
PMA × manipulated attribute	0.01	0.06	[−0.11, 0.14]	.819
PMA × direction × manipulated attribute	0.16	0.12	[−0.08, 0.40]	.199

Note. Variables were coded as follows—direction: −0.5 = low, + 0.5 = high; attribute: −0.5 = benefit, + 0.5 = risk. CI = confidence interval.

Exploratory Analysis: Mediation Effects. We also tested whether the effect of the experimental manipulation on change in the non-manipulated attributes was mediated by the changes in the manipulated attribute as the analytic reasoning would suggest. To do this, we conducted a multilevel mediation analysis (this analysis was not part of the pre-registration). Bayesian estimation of the multilevel mediation model was performed using the *bmlm* R package (Vuorre & Bolger, 2018). Because our experimental design involved two directions (High vs. Low), we conducted two independent mediation analyses that looked at the responses within High and Low separately. Indeed, both sets of mediation analysis show a significant indirect effect of manipulation on non-manipulated attribute rating through manipulated attribute rating (High only mediation: $M_{posterior}$ = −0.54, $SD = 0.04$, CI = [−0.61, −0.47]; Low only mediation: $M_{posterior} = 0.55$, $SD = 0.04$, $CI =$ [0.48, 0.62]). For details results see Table S25–S26 in the supplementary material.

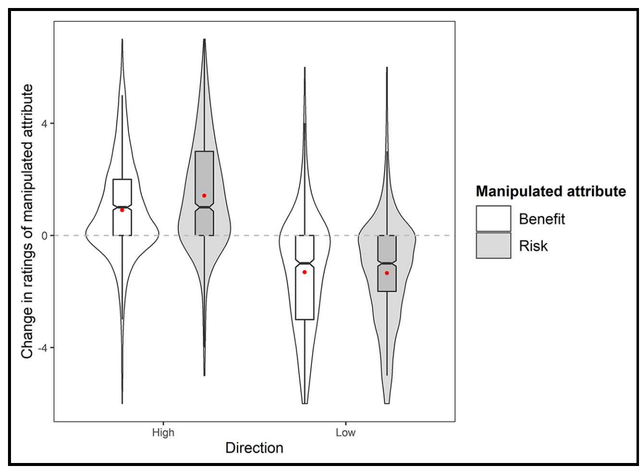

Figure 2. Distribution of Ratings on Change in Manipulated Attribute as DV by Experimental Conditions.
Note. Figure includes violin plots displaying the distribution of responses, boxplots displaying the median, first, and third quartiles, while the mean value is identified by the red circle.

Extensions

Naturally Occurring Incidental Mood and the Negative Relationship Between Risks and Benefits. We conducted an analysis where the change in ratings of manipulated attributes, level of pleasure, level of arousal, and their interaction were set as predictors of change in the ratings of the non-manipulated attributes. Table 4 and Figure 4 summarize the results. As a representation of the negative relationship between risks and benefits, we looked at predicting change in non-manipulated attribute with change in manipulated attribute. Indeed, a negative correlation between these two variables represents the negative relationship. We decided to use this (rather than an interaction between the dummy coded direction and manipulated attribute), as it is easier to represent and interpret a potential two-way interaction with pleasure or arousal.

We found some support that the negative relationship is moderated by incidental pleasure (see Figure 4). Specifically, the negative relationship was stronger among participants who reported higher incidental pleasure in comparison to participants who reported lower incidental pleasure.

Risk/Benefit Strength. We also examined whether there was a stronger negative relationship when risks, as opposed to benefits were manipulated and the extent to which it may depend on the manipulated conditions. For the analysis, similar to above, we again used the change in ratings of manipulated attributes, Manipulated Attribute (Risk vs. Benefit), Direction, and their interaction as predictors of change in the ratings of the non-manipulated attributes. Table 5 and Figure 5 summarize the results.

The interaction between manipulated attribute and CMA (change in manipulated attribute) indicates that the

Table 3. Estimated Fixed-Effects Coefficients of the Mixed-Effects Regression Model With Change in the Non-Manipulated Attribute as the DV.

Predictors	DV: Change in non-manipulated attribute			
	B	*SE*	95% CI	*p*
Intercept	−0.26	0.10	[−0.45, −0.06]	**.009**
Pre-rating manipulated attribute (PMA)	−0.21	0.03	[−0.27, −0.15]	**<.001**
Pre-rating non-manipulated attribute (PNMA)	−0.95	0.03	[−1.01, −0.89]	**<.001**
Direction (high vs. low)	−1.15	0.06	[−1.27, −1.03]	**<.001**
Attribute (risk vs. benefit)	0.55	0.06	[0.43, 0.67]	**<.001**
PNMA × Direction	0.14	0.05	[0.04, 0.25]	**.008**
PNMA × Attribute	−0.16	0.06	[−0.27, −0.05]	**.004**
Direction × Attribute	−1.34	0.12	[−1.58, −1.10]	**<.001**
PNMA × Direction× Attribute	0.13	0.11	[−0.08, 0.35]	.221

Note. Variables were coded as follows—direction: −0.5 = low, + 0.5 = high; attribute: −0.5 = benefit, + 0.5 = risk. CI = confidence interval.

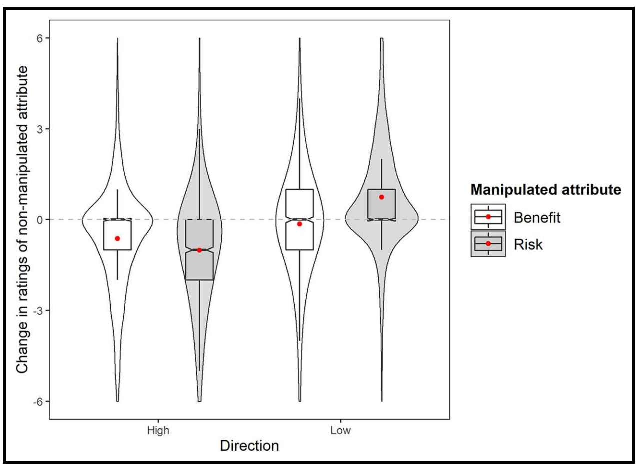

Figure 3. Distribution of Rating on Change in Non-Manipulated Attribute as DV by Experimental Conditions.
Note. Figure includes violin plots displaying the distribution of responses, boxplots displaying the median, first, and third quartiles, while the mean value is identified by the red circle.

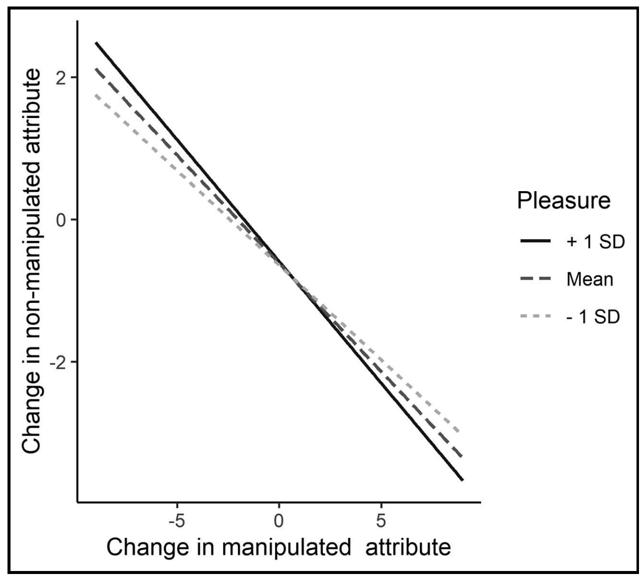

Figure 4. The Interaction Between Change in Manipulated Attribute and Pleasure on Change in Non-Manipulated Attribute

strength of the negative relationship between the manipulated and non-manipulated attribute was stronger when risks, as opposed to benefits, were manipulated. Furthermore, the three-way interaction (Direction × Manipulated Attribute × CMA) suggests that the extent of difference between risks and benefits varies as a function of the direction of manipulation (High vs. Low). Proceeding to conduct separate analyses for Low and High conditions, results within the high condition show no support for interaction. However, results within the low condition do find support for the interaction (See Table S32 and Table S33 in the supplementary material for detailed results). This lack of consistency leads us to conclude that the strength of the negative relationship between the manipulated and the non-manipulated attribute being stronger when risks, as opposed to benefits, were manipulated is mainly driven by participants' responses within the Low-Benefit condition (see Figure 5). Specifically, we note large differences in change in ratings of non-manipulated attribute across Risk, M_{change} = 0.74 (SE = 0.05) and Benefit, M_{change} = −0.14, (0.05), manipulation within the low condition. However, those differences are much smaller within the high condition, Risk: M_{change} = −1.01 (0.06); Benefit: M_{change} = −0.62, (0.05).

General Discussion

In two studies, using samples from the United States and the United Kingdom, we re-did Study 2 from Finucane et al. (2000). With high power and using a more precise analytic approach, we successfully replicated and obtained a similar effect as in the original study providing support

Table 4. Estimated Fixed-Effects Coefficients From the Mixed-Effects Regression Model Adding Pleasure and Arousal Measures on Change in Non-Manipulated Attribute as DV.

Predictors	DV: Change in non-manipulated attribute			
	B	*SE*	95% CI	*p*
Intercept	−0.59	0.15	[−0.88, −0.29]	**<.001**
Pre-rating non-manipulated attribute (PNMA)	−0.63	0.05	[−0.72, −0.54]	**<.001**
Pre-rating manipulated attribute (PMA)	−1.05	0.04	[−1.13, −0.97]	**<.001**
Pleasure	0.03	0.05	[−0.07, 0.13]	.557
Arousal	−0.06	0.05	[−0.16, 0.04]	.266
Change in manipulated attribute (CMA)	−0.70	0.05	[−0.79, −0.61]	**<.001**
Direction (high vs. low)	0.30	0.09	[0.13, 0.48]	**.001**
Manipulated attribute (risk vs. benefit)	0.39	0.08	[0.23, 0.56]	**<.001**
Pleasure × Arousal	−0.02	0.03	[−0.08, 0.04]	.536
Pleasure × CMA	−0.09	0.04	[−0.16, −0.01]	**.025**
Arousal × CMA	0.05	0.04	[−0.04, 0.13]	.293
Pleasure × Arousal × CMA	−0.03	0.03	[−0.09, 0.02]	.201

Note. CI = confidence interval.

Table 5. Estimated Fixed-Effects Coefficients From the Mixed-Effects Regression Model Looking at Moderation of the Negative Relationship by Risks/Benefits.

Predictors	DV: Change in non-manipulated attribute			
	B	*SE*	95% CI	*p*
Intercept	−0.24	0.13	[−0.49, 0.02]	.066
Pre-rating manipulated attribute (PMA)	−0.59	0.03	[−0.65, −0.53]	**<.001**
Pre-rating non-manipulated attribute (PNMA)	−1.01	0.03	[−1.06, −0.95]	**<.001**
Direction (high vs. low)	−0.37	0.06	[−0.49, −0.24]	**<.001**
Manipulated attribute (risk vs. benefit)	0.44	0.06	[0.31, 0.56]	**<.001**
Change in manipulated attribute (CMA)	−0.74	0.03	[−0.80, −0.68]	**<.001**
Direction × Manipulated Attribute	−0.85	0.12	[−1.09, −0.60]	**<.001**
Direction × CMA	−0.12	0.05	[−0.23, −0.02]	**.022**
CMA × Manipulated Attribute	−0.27	0.05	[−0.37, −0.16]	**<.001**
Direction × Manipulated Attribute × CMA	0.22	0.11	[0.01, 0.43]	**.037**

Note. Variables were coded as follows—direction: −0.5 = low, + 0.5 = high; attribute: −0.5 = benefit, + 0.5 = risk. CI = confidence interval.

for the demonstration of a causal negative relationship between risks and benefit judgments. Specifically, we showed that increasing the risks of three technologies (nuclear energy, food preservatives, and natural gas) led to lower judgments on benefits while increasing the benefits led to lower judgments on risks. Vice versa, decreasing risks led to higher judgments of benefits. However, we did not find any differences in the low-benefit conditions. Specifically, decreasing the benefits did not lead to higher judgments of risks (See Table S41–S44 in the supplementary material for detailed results).

In addition, we report two extensions. First, we found that the negative relationship between risks and benefits was stronger among participants who reported feeling higher incidental pleasure. Concurrently, people who felt pleasant may have generally relied more on heuristic processing—in this case the AH (Bohner et al., 1995). Previous findings, which manipulated negative mood, showed increased risk perceptions (Västfjäll et al., 2014). This may indicate that negative mood has a more pointed effect on risk-benefit judgments, although our findings cannot speak on this as we did not have a lot of data on the negative side of our measures, meaning we had few participants feeling low pleasure and low arousal (see Figure S5 in the supplementary material). This may have reduced our chances of obtaining more precise findings on how incidental affect can modulate the negative relationship. Furthermore, it is important to note that we measured naturally occurring incidental mood whereas previous research manipulated mood directly.

Second, we looked at whether manipulating risks or manipulating benefits impacts the strength of the negative relationship. Initially, our results showed the strength of the negative relationship was stronger when risks, as opposed to benefits, were manipulated. However, a more detailed look shows that this effect is most likely a product of the fact that there was no impact on the non-manipulated attribute in the low-benefit condition (see

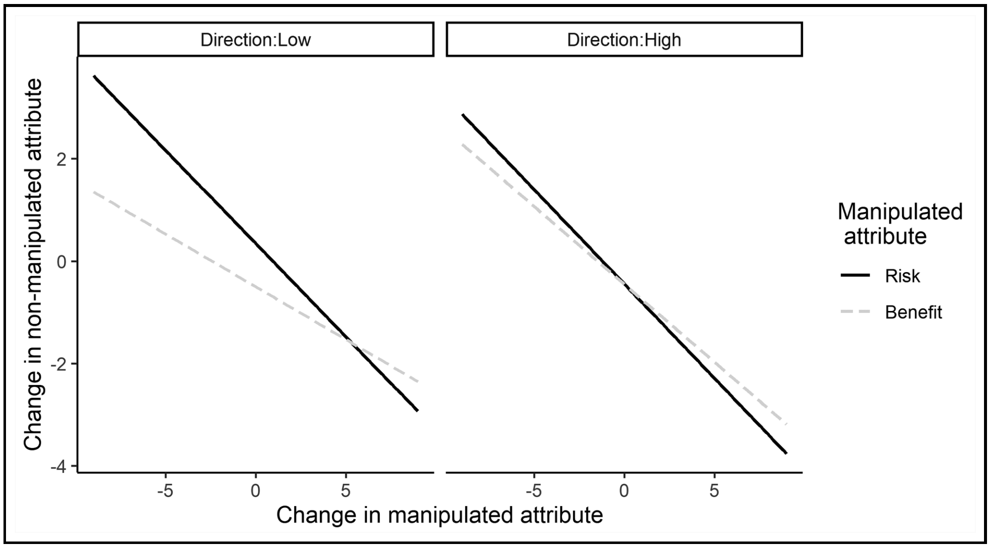

Figure 5. Relationship Between Manipulated and Non-Manipulated Attributes as a Function of Risk/Benefit Manipulations

Table S41–S44; the original findings seem to show this as well; see Table S34 and Table S35 in the supplementary material for detailed results). It is worth pointing out that manipulating low benefits did lead to a predicted change in benefits—people judged them as considerably lower (i.e., there was a successful manipulation; see Table S41–S44). But decreasing benefits did not lead to the predicted impact on risks. This may hint at the fact that providing low benefit info is not enough to lead to perceptible changes in affect as it may be that risks are simply better at evoking an affective reaction (cf. Pachur et al., 2014). Our results also hint at the fact that people may pay more attention to risks—both increase and decrease in risks—while this is not the case for benefits, where only increase in benefits led to perceivable changes. Alternatively, the lack of impact on the non-manipulated attribute in the low-benefit condition may hint at sensitivity to the actual relationship of risks and benefits in the world, namely, that they are often positively correlated. As mentioned in the introduction, technologies low in benefit are unlikely to be high in risk. It is of course not incommensurable that this sensitivity exists along a strong affective process that leads to negative relationships between risks and benefits.

Current findings may have important implications for risk communication (Thaler & Sunstein, 2008; Yang et al., 2014). For instance, communication efforts about new technologies ought to contend that risk information may overweigh other benefit information and is more malleable to manipulate. While out of scope for this research, it may be worth taking a closer look at what associations people might have with the terms "risky" and "beneficial." Specifically, people may already associate and interpret these terms as "bad" (for risky) and "good" (for beneficial), explaining the negative correlation.

We believe this replication strengthens the claim that it is possible to causally affect risk and benefit judgments. The negative relationship has been presented as a demonstration of the AH. However, while the effect is *consistent* with an AH, we (as the original finding) do not provide direct evidence that affect does mediate this negative relationship. Indeed, the negative relationship could also occur due to a more cognitive explanation. While we show evidence that change in the manipulated attribute is a mediator between the manipulations and non-manipulated attribute, this may be one of the potential mediators and the underlying cause remains uncovered. Some recent research has, for example, found more support for manipulations of availability by the recall, rather than affect, to have a stronger impact on how risk judgments are constructed (Efendić, 2021). Nevertheless, with this replication, we hope to encourage future researchers that this paradigm is robust and could potentially be used to tease apart any cognitive/affective explanations of risk/benefit judgments.

Finally, in our replication, we focused on the original three technological scenarios as the risky hazards. While one could argue that people's attitudes toward these risks have changed in the intervening 20 years since the original study, impacting the strength of the negative relationship, our results show similar effects. This could indicate that either the attitudes did not change, or, equally likely, that the manipulations of risk/benefit go well and beyond beliefs and attitudes. In that sense, future work should look at whether the negative relationship extends to other hazards. For instance, Skagerlund et al. (2020) found that the inverse relationship extends to numerous other hazards, activities, and technologies.

Author Contributions

G.F. led the project, supervised each step of the project, conducted the pre-registration, and ran data collection. E.E. and S.P.C. followed up on initial work by the other coauthors to verify and conduct additional analyses, and completed the manuscript draft. E.E., S.P.C., and G.F. jointly finalized the manuscript for submission. C.S.L., L.Y.Y., M.J.K., and C.Y.L. conducted the replication and extension as part of university course work. They conducted an initial analysis of the paper, designed the replication, initiated the extensions, wrote the pre-registration, conducted initial data analysis, and wrote initial replication reports.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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Supplemental Material

The supplemental material is available in the online version of the article.

Notes

1. We would like to thank the original authors for providing the materials.
2. Note that the preregistrations follow a registered report format. This means that a manuscript-like document was produced reporting simulated random data results. Please see also the Read-me document in the wiki page on the OSF preregistrations here: https://osf.io/pg3ae/ for a detailed guide on where to find information on preregistered materials, design, and analysis plan.
3. Indicating a low proficiency of English, self-report not being serious about filling in the survey, who guessed the hypothesis, have done the survey before, who failed to complete the survey, and those not from the United States/ United Kingdom. Please see Table S2 in the supplement for more detail.
4. We ran all the models below with study included as a fixed effect and we did not find any evidence that the results differed between studies. Please see tables S9, S13, S18, and S23 in the supplement.
5. The additional experimental condition presented participants both information on risk *and* benefit. This presentation made it impossible to test the negative relationship and we saw fit to exclude it. Some 192 of the 968 participants in the prolific sample were in the excluded condition. Responses from remaining 776 prolific participants was included in the final analysis. Please see also note 2 in Table S1 and Table S5 in supplement for more details.
6. In the original study, the question added the phrasing ". . . to U.S. society as a whole" at the end. We used this exact phrasing in the MTurk sample (which included people from the United States) but decided to exclude this for the Prolific sample as these participants were from the United Kingdom.

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Finucane et al. (2000): Replication and extension: Supplementary

Contents

Disclosures

Data collection

Data collection was completed before analyzing the data.

Conditions reporting

We report all the conditions we collected.

Variables reporting

All variables collected for this study are reported and included in the provided data.

Exclusion criteria for the two replication studies

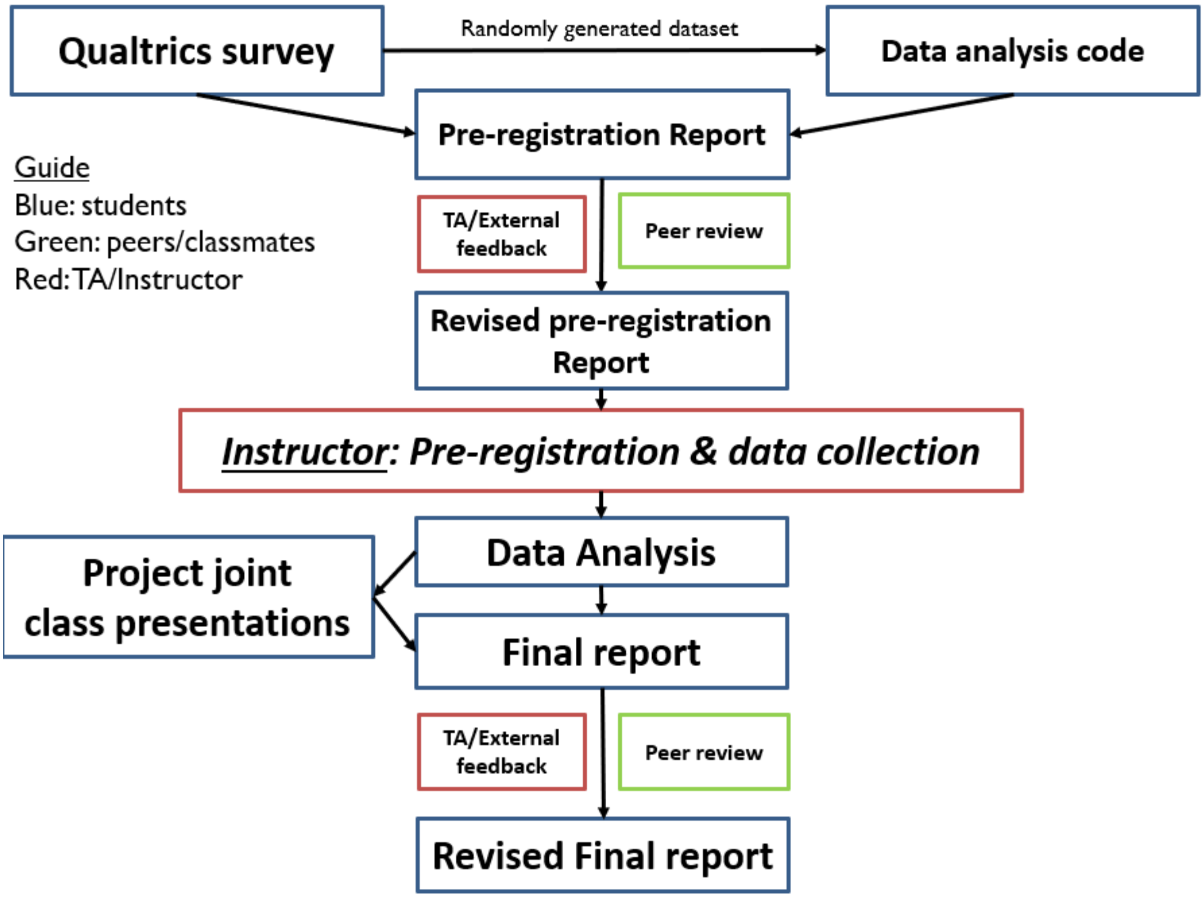
1. Subjects indicating a low proficiency of English (self-report < 5, on a 1-7 scale);
2. Subjects who self-report not being serious about filling in the survey (self-report < 4, on a 1-5 scale);
3. Subjects who correctly guessed the hypothesis of this study in the funnelling section;
4. Have seen or done the survey before;
5. Subjects who failed to complete the survey. (duration = 0, leave question blank);
6. Not from the United States/UK;

Project Process Outline

The current replication is part of the mass pre-registered replication project, with the aim of revisiting well-known research findings in the area of judgment and decision making (JDM) and examining the reproducibility and replicability of these findings.
The current replication followed the same project outline as noted below. For each of the replication projects, researchers completed full pre-registrations, data analysis, and APA style submission-ready reports. The authors independently reproduced the materials and designed the replication experiment, with a separate pre-registration document. The researchers then peer-reviewed one another to try and arrive at the best possible design. Then, the lead and corresponding authors reviewed the integrated work and the last corresponding author made final adjustments and conducted the pre-registration and data collection.

The OSF page of the project contains one Qualtrics survey design used for data collection with pre-registration documents submitted by each of the researchers. In the manuscript, we followed the most conservative of the pre-registrations.

Figure S1. *Project process diagram*



Verification of Analyses

Initial analyses were conducted by the independent researchers, who used JAMOVI (jamovi project, 2018) or R for data analyses. In preparing this manuscript, the lead and corresponding authors verified the analyses in R.

Sample comparison between original and our two studies

Table S1. Sample differences and similarities between original study and our replications

	Original	American MTurk workers	Prolific workers
Sample size[1]	219	776	968[2]
Geographic origin	University of Oregon, United States	US American	US American
Gender	112 males, 107 females	411 males, 363 females, 2 other/ would rather not disclose	401 males, 566 females, 1 other/ would rather not disclose
Average age (years)	21	38.01	39.64
SD (years)	N/A	11.16	13.14
Medium (location)	N/A	Online	Online
Compensation	N/A	Nominal payment	Nominal payment
Year	2000[3]	2019	2019

[1] We note the final sample size after exclusions.
[2] Please note that the Prolific sample included an extra between-subject condition that was aimed as an extension. However, we did not include this condition in the analysis as we found it difficult to draw conclusions from the results. We initially intended this extension to serve as a mixed condition, showing both risks and benefit information. However, we found it difficult to draw any reliable conclusions from this condition. Given that this condition was not pertinent, upon review, we decided not to include this exploratory extension condition in our reporting, though it is included in our shared data and code for those interested in further analyses. Thus, the 192 participants assigned to this condition were excluded leaving us with total of 776 participants in the Prolific sample as well. The equal number of participants between the two samples is purely due to chance. Please refer to Table S5 for a description of what participants read in the extension condition.
[3] Manucript was published during the year 2000, but the data collection time is unspecified in the original article.

Power analyses

Using G*Power (Fual et al., 2007), we conducted a power analysis to determine the sample size necessary to replicate the results described in Study 2 of Finucane et al. (2000). We based the power analysis on the t-values of each individual condition (affective information) – see “Original article’s results” section reported below in this document. Given our resource constraints, we wanted to at least ensure we were able to detect the weakest effect size reported in the original study *that was also significant* (at $p < .05$). See Table S2 below. Finally, we aimed for a higher sample size between 750 to 800 participants, as this would also ensure we were able to detect a smaller effect size (Cohen’s d_z) of .20 at .80 power.

Table S2. Sample size calculations, location of power analyses, and location of exclusion criteria for the two independent Pre-registrations, as reported in the OSF pages.

Authors	Preregistration detail	
Group A	Power analysis: Required sample size	556
	URL of the power analysis document	https://osf.io/mhekr/ (please refer to page number 29-31)
	Extension or Additional variables	Yes, naturally occurring incidental mood and the AH
	Exclusion criteria	Yes. Please refer to page no. 42.
Group B	Power analysis: Required sample size	308
	URL of the power analysis document	https://osf.io/wcrkj/ Please refer to page number 13.
	Extension or Additional variables	Yes, extra between-subject condition, removed. See Table S1.
	Exclusion criteria	Yes. Please refer to page no 22

Materials and scales used in the original experiment

Type of study

Experimental Manipulations (Mixed design).

Experimental design

Table S3. Experimental Design of the Original Experiment

	Affective Information			
	High Benefit	High Risk	Low Benefit	Low Risk
	Initial Judgment: Before reading the affective information (Answering 4 questions on each technology, 12 questions in total)[2]			
Technology Scenarios				
Nuclear Power[1]	Final Judgment: After reading the designated affective information of **Nuclear Power** (4 questions)[2]			
Natural Gas[1]	Final Judgment: After reading the designated affective information of **Natural Gas** (4 questions)[2]			
Food Preservatives[1]	Final Judgment: After reading the designated affective information of **Food Preservatives** (4 questions)[2]			

[1] The order of presentation of the technologies was not specified in the original experiment. The presentation was randomized in our replication studies.

[2] See Table S4 for the full description of the questions.

Participants were randomly assigned to one of the four affective information conditions. Before reading the affective information, participants were asked to provide their initial judgment on nuclear power, natural gas, and food preservatives. For each technology, they were asked to answer a set of 4 questions regarding perceived risk and benefit (see Table S4).

After that, dependent on the affective information condition, they read the affective information about each technology and provided the final judgment by answering the same set of questions as in their initial judgment. The order of presenting the evaluation questions and vignettes was not specified in the original paper but was randomized in our replication studies. We conducted an additional analysis to check for any order effects (i.e., did the presentation order of technology scenario influence ratings for both non-manipulated and manipulated attributes). We do not find any support for order effects.

Dependent variables

1. Initial Judgment: Prior to the presentation of the affective information

   Before the participants received the affective information of the technologies (nuclear power, natural gas, and food preservatives) from the experimenter, they were asked to evaluate these technologies regarding their perceived risk and benefit (4 questions for each technology scenario) on a 10-point scale.

   The example given in the original paper on the natural gas condition was “In general, how beneficial do you consider the use of natural gas to be to US society as a whole?”. Participants were asked to answer the question on a 10-point scale from “not at all beneficial” to “very beneficial” We used the same wording and scale in the MTurk sample (which had participants from the US) while the later part of the question (“to US society as a whole") was not included in the Prolific sample (which had participants form the UK).

Table S4. Questions used in the Original Experiment

Order[1]	Judgment question on perceived risk and benefit — 10-point scale
1	In general, how beneficial do you consider the use of nuclear power[2] to be to U.S. society as a whole?
	From 1 "not at all beneficial" to 5 "moderate benefit" to 10 "very beneficial"
2	In general, how risky do you consider the use of nuclear power[2] to be to U.S. society as a whole?
	From 1 "not at all risky" to 5 "moderate risk" to 10 "very risky"
3[3]	How likely do you think it is that there will be a major accident or problem (and consequently serious harm to people) within the next 5 years as a result of using nuclear power[2]?
	From 1 "very unlikely" to 10 "very likely"
4[3]	To what extent can the risks of using nuclear power[2] be controlled by those who are exposed to those risks?
	From 1 "very little control" to 10 "very much control"

[1] The order of the first two questions was believed to be randomized and presented evenly.
[2] The factor underlined above was substituted to "natural gas" and "food preservatives" depending on the condition
[3] Questions 3 and 4 were asked in the original paper, but it appears as they were not of relevance for the hypothesis so they were not reported.

2. Final Judgment: After Reading the Affective Information

   The questions used in the final judgment were identical to the questions in the initial judgment. The participants were again asked to judge the perceived risk and benefit of each technology. The order of presenting the judgment questions was not specified in the original but was randomized in our replication studies. By making reference to the original experimental material, we believe that the order of Question 3 and 4 was fixed, while the order of Question 1 and 2 was dependent on the condition. In risk conditions, Question 2 (risk judgment) was presented first; in the benefit conditions, Question 1 (benefit judgment) was presented first.

Risk / Benefit descriptions, i.e., the affective information

See OSF for the original paper questionnaire used and the affective information presented to the participants across the conditions. We used the same descriptions as in the original article.

Comprehension checks

No comprehension check was mentioned in the original paper. Therefore, we decided not include comprehension checks in the replication studies.

Data gathering

There are variations in the physical settings. In the original study, the participants had to fill in a paper questionnaire under the supervision of the experimenters; in the current replication, the participants responded to a Qualtrics survey online, using their own electronic devices.

Extension scenario related to prolific sample

Participants in the Prolific sample assigned to Extension condition first reported the initial risks and benefits ratings on three technologies and proceeded to read descriptions about each technology (see table below) that contained information about both risks *and* benefits. After reading the vignette content, participants again provided answers to the risk and benefit questions for each technology scenario.

Table S5. Scenario descriptions of the removed experimental condition in the Prolific sample

Affective Information	Technology	Vignette content
Extension condition	Nuclear Power	Nuclear power has a good safety record and an accident rate that is comparable with other industries that produce electricity. Part of the reason that risks have been low in the nuclear power industry is that the industry is heavily monitored and regulated by the federal government. All nuclear power plants have on-site federal regulators. The plants are also built to resist accidents. Even the most serious nuclear accident in United States history, Three Mile Island, did not harm anyone's health. On the other hand, nuclear power today produces only a small percentage of our nation's electricity. New methods of generating electricity, such as geothermal, solar power, and wind turbines, could eventually replace nuclear power. In addition, the application of energy-conservation methods could save more energy than is produced by nuclear power. Finally, the addition of electrical generators to the boilers of factories all over the United States could produce more power than is supplied by nuclear power, without the construction of any more plants of any sort.
	Natural Gas	Natural gas is one of the safest forms of energy. Accidents involving natural gas have been very rare. Modern gas pipelines and transportation networks have been constructed to high standards and are regulated by both state and federal government agencies. Today's appliances that use natural gas have been constructed to reduce the chance of accidents, with formerly dangerous items, such as pilot lights, replaced by electronic ignition of the gas. In addition, natural gas detectors are now available to warn consumers of any potential danger and home accidents are now almost unheard of. Natural gas was once almost free, since it was frequently discovered as a by-product during the drilling of oil wells. Today this is no longer true and natural gas costs ever increasing amounts of money to discover, develop and transport. It is possible to transport natural gas through the use of pipelines and liquefaction. However, compared to the ease with which other forms of energy, especially electricity, can be transported, the transportation of natural gas is not efficient.
	Food Preservatives	Food preservatives are chemicals added to food. The risks of food preservatives are much less than the risks from traditional methods of preservation, such as smoking or salting, which have been shown to cause such severe health effects as hypertension and cancer. In addition, the risk from food preservatives is very small when compared to the risk of eating

		food that has started to spoil. The question today is: Are they still necessary? In most parts of the country rapid transportation, refrigeration, freezing, and the availability of locally produced food products makes it possible to get foods to market and to people's homes without using any preservatives at all. The amount of a preservative used in food is far too small to be a danger to people. Before a food preservative can be used in the United States it must pass years of tests to make sure that it will not cause illness in consumers. Although food preservatives have played an important role in the past, it appears that the need to use preservatives is declining today.

Additional results based on new data-analysis strategy

Table S6. Descriptive statistics of combining both Mturk and Prolific sample

		Initial Assessment			Assessment after manipulation		
Scenario		*M*	*SD*	*Med*	*M*	*SD*	*Med*
High Benefit (n = 391)							
Food Preservatives	Benefit	6.38	2.32	7	7.45	2.16	8
	Risk	5.16	2.37	5	4.45	2.34	4
Natural Gas	Benefit	7.34	2.05	8	7.95	1.90	8
	Risk	4.97	2.28	5	4.55	2.27	4
Nuclear Power	Benefit	6.68	2.44	7	7.69	2.11	8
	Risk	6.71	2.58	7	5.96	2.65	6
Low Benefit (n = 387)							
Food Preservatives	Benefit	6.46	2.30	7	5.27	2.31	5
	Risk	4.92	2.13	5	4.78	2.14	5
Natural Gas	Benefit	7.24	2.03	7	5.86	2.35	6
	Risk	4.93	2.13	5	5.13	1.99	5
Nuclear Power	Benefit	6.60	2.57	7	5.24	2.60	5
	Risk	6.88	2.50	7	6.38	2.54	6
High Risk (n = 385)							
Food Preservatives	Benefit	6.39	2.29	7	5.37	2.43	5
	Risk	4.98	2.22	5	6.35	2.34	7
Natural Gas	Benefit	7.09	2.23	7	5.91	2.29	6
	Risk	5.03	2.34	5	6.92	2.24	7
Nuclear Power	Benefit	6.67	2.39	7	5.83	2.73	6
	Risk	6.55	2.56	7	7.53	2.48	8
Low Risk (n = 389)							
Food Preservatives	Benefit	6.47	2.24	7	7.36	2.15	8
	Risk	5.07	2.18	5	3.81	2.13	3
Natural Gas	Benefit	7.05	2.08	7	7.67	1.94	8
	Risk	4.92	2.20	5	3.79	2.12	3
Nuclear Power	Benefit	6.53	2.51	7	7.25	2.24	8
	Risk	6.75	2.42	7	5.11	2.50	5

Figure S2. Pre-treatment risk and benefits ratings across each of the three technologies (and combined)

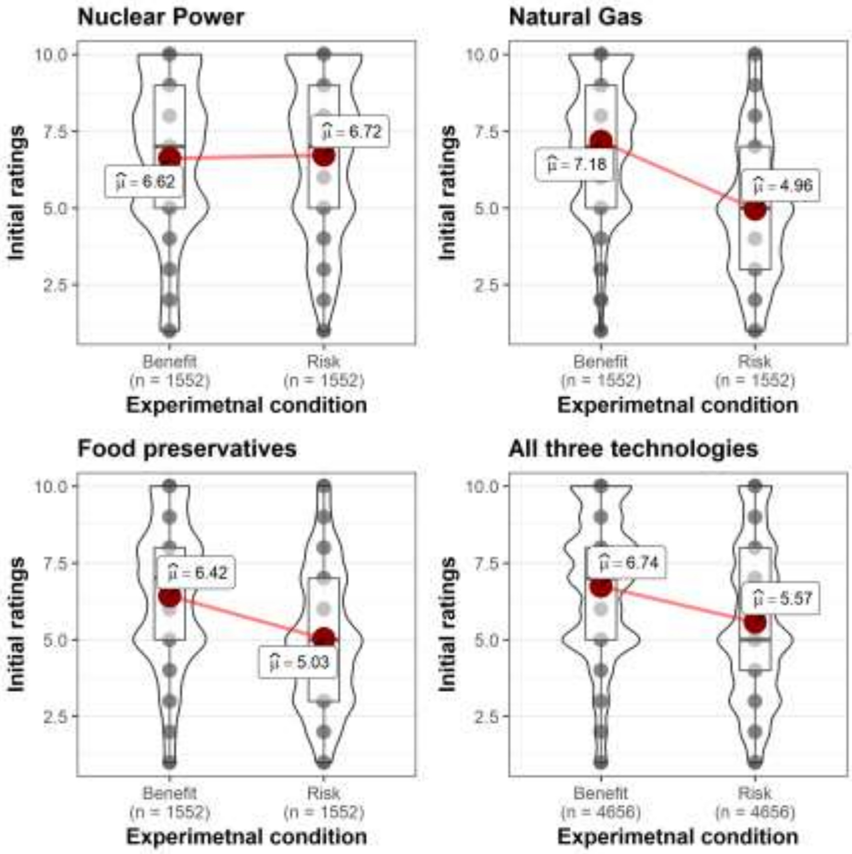
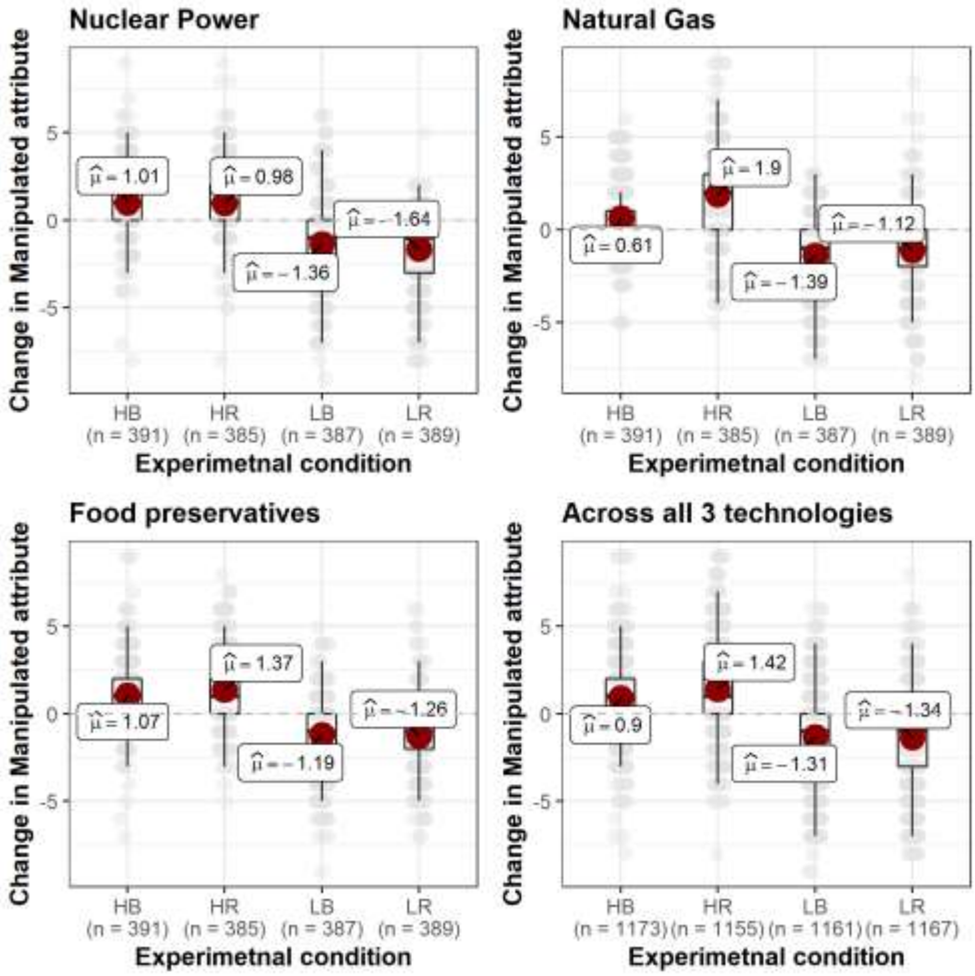
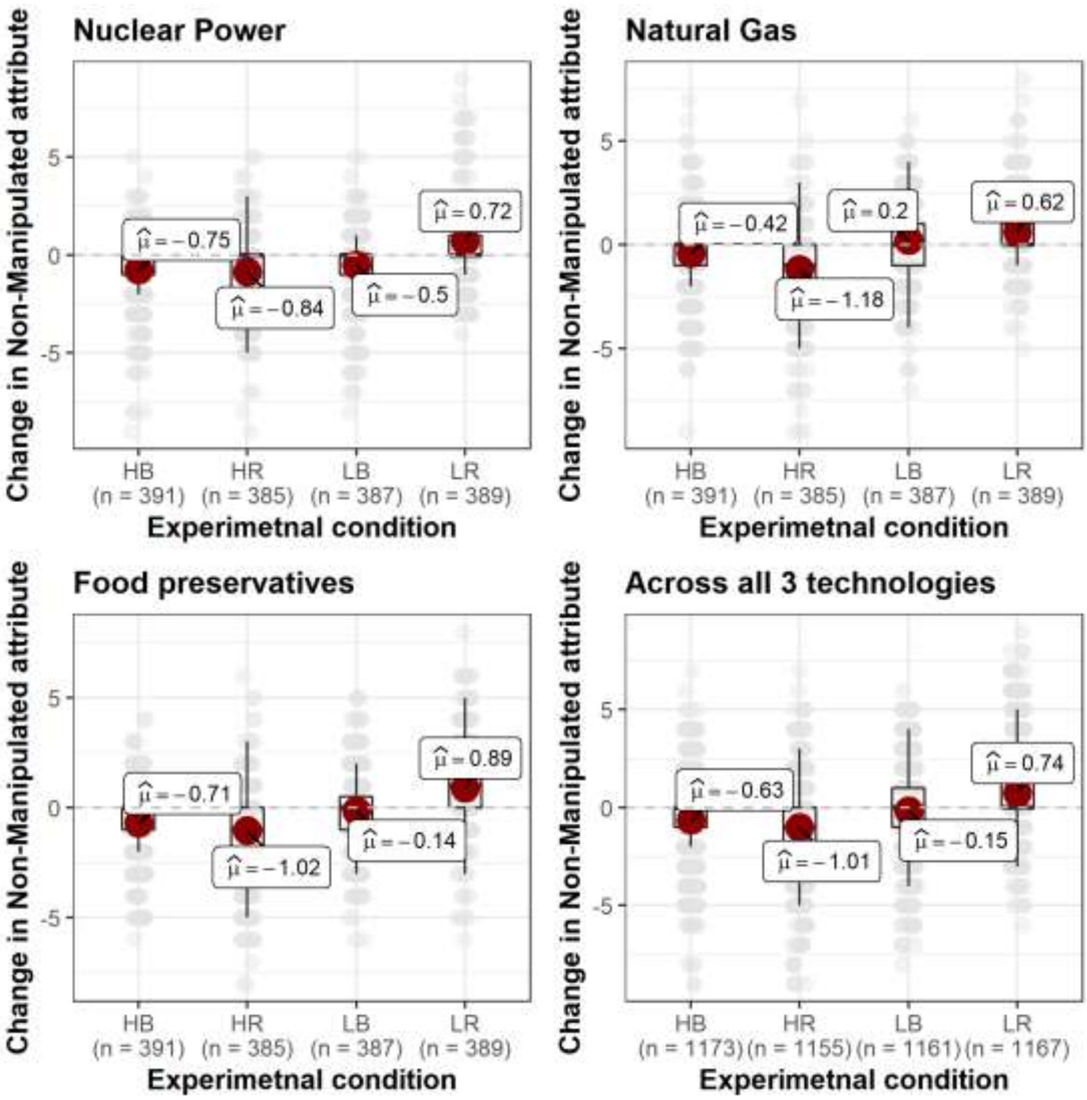


Figure S3. Change in ratings of manipulated attributes across each of the three technologies (and combined)



Note. HB = High benefit; HR= High risk; LB = Low benefit; LR = Low risk

Figure S4. Change in ratings of non-manipulated attributes across each of the three technologies (and combined)



Note. HB = High benefit; HR= High risk; LB = Low benefit; LR = Low risk

Table S7. Results of linear mixed-effects regression as part of manipulation verification. (Dependent variable: Ratings on manipulated attribute after treatment)

	Model 1				Model 2				Model 3			
Predictors	***B***	***S.E.***	***CI***	***p***	***B***	***S.E.***	***CI***	***p***	***B***	***S.E.***	***CI***	***p***
(Intercept)	6.08	0.20	5.69 – 6.48	**<0.001**	6.08	0.07	5.94 – 6.23	**<0.001**	6.08	0.07	5.94 – 6.23	**<0.001**
Pre-rating manipulated attribute (PMA)					1.33	0.03	1.27 – 1.38	**<0.001**	1.32	0.03	1.25 – 1.38	**<0.001**
Direction (High vs. Low)												
Attribute (Risk vs. Benefit)												
Direction × Attribute												
PMA ×Direction												
PMA ×Attribute												
PMA × Direction × Attribute												
Random Effects												
σ^2	3.24				2.23				1.9			
τ_{00}	3.83 $_{\text{ParticipantID}}$				2.62 $_{\text{ParticipantID}}$				5.65 $_{\text{ParticipantID}}$			
	0.11 $_{\text{Tech\_type}}$				0.01 $_{\text{Tech\_type}}$				0.01 $_{\text{Tech\_type}}$			
τ_{11}									0.06 $_{\text{ParticipantID.PMA}}$			
ρ_{01}									-0.73 $_{\text{ParticipantID}}$			
ICC	0.55				0.54				0.75			
N	1552 $_{\text{ParticipantID}}$				1552 $_{\text{ParticipantID}}$				1552 $_{\text{ParticipantID}}$			
	3 $_{\text{Tech\_type}}$				3 $_{\text{Tech\_type}}$				3 $_{\text{Tech\_type}}$			
Observations	4656				4656				4656			
Marginal R^2 / Conditional R^2	0.000 / 0.549				0.266 / 0.663				0.187 / 0.796			
AIC	21058.289				19303.531				19208.559			
log-Likelihood	-10525.144				-9646.766				-9597.28			

Note: Variables were coded as follows—Direction: -0.5 = Low, +0.5= High; Attribute: -0.5 = Benefit, +0.5= Risk;

Table S8. Results of linear mixed-effects regression as part of manipulation verification. (Dependent variable: Ratings on manipulated attribute after treatment)

	Model 4				Model 5				Model 6			
Predictors	***B***	***S.E.***	***CI***	***p***	***B***	***S.E.***	***CI***	***p***	***B***	***S.E.***	***CI***	***p***
(Intercept)	6.08	0.06	5.96 – 6.20	**<0.001**	6.08	0.06	5.96 – 6.21	**<0.001**	6.08	0.06	5.96 – 6.21	**<0.001**
Pre-rating manipulated attribute (PMA)	1.39	0.03	1.33 – 1.45	**<0.001**	1.37	0.03	1.31 – 1.43	**<0.001**	1.37	0.03	1.31 – 1.43	**<0.001**
Direction (High vs. Low)	2.53	0.07	2.40 – 2.67	**<0.001**	2.54	0.07	2.40 – 2.67	**<0.001**	2.56	0.07	2.42 – 2.69	**<0.001**
Attribute (Risk vs. Benefit)					-0.27	0.07	-0.40 – -0.13	**<0.001**	-0.27	0.07	-0.40 – -0.13	**<0.001**
Direction × Attribute					0.53	0.13	0.27 – 0.80	**<0.001**	0.49	0.14	0.22 – 0.75	**<0.001**
PMA ×Direction									-0.10	0.06	-0.22 – 0.02	0.109
PMA ×Attribute									0.01	0.06	-0.11 – 0.14	0.819
PMA ×Direction × Attribute									0.16	0.12	-0.08 – 0.40	0.199
Random Effects												
σ^2	1.91				1.91				1.91			
τ_{00}	3.68 $_{\text{ParticipantID}}$				3.62 $_{\text{ParticipantID}}$				3.63 $_{\text{ParticipantID}}$			
	0.01 $_{\text{Tech\_type}}$				0.01 $_{\text{Tech\_type}}$				0.01 $_{\text{Tech\_type}}$			
τ_{11}	0.06 $_{\text{ParticipantID.PMA}}$				0.06 $_{\text{ParticipantID.PMA}}$				0.06 $_{\text{ParticipantID.PMA}}$			
ρ_{01}	-0.85 $_{\text{ParticipantID}}$				-0.85 $_{\text{ParticipantID}}$				-0.85 $_{\text{ParticipantID}}$			
ICC	0.66				0.65				0.66			
N	1552 $_{\text{ParticipantID}}$				1552 $_{\text{ParticipantID}}$				1552 $_{\text{ParticipantID}}$			
	3 $_{\text{Tech\_type}}$				3 $_{\text{Tech\_type}}$				3 $_{\text{Tech\_type}}$			
Observations	4656				4656				4656			
Marginal R^2 / Conditional R^2	0.387 / 0.791				0.394 / 0.791				0.394 / 0.791			
AIC	18238.874				18218.089				18229.772			
log-Likelihood	-9111.437				-9099.045				-9101.886			

Note: Variables were coded as follows—Direction: -0.5 = Low, +0.5= High; Attribute: -0.5 = Benefit, +0.5= Risk;

Table S9. Comparisons of intercept only models (Dependent variable: Ratings of manipulated attribute after treatment). Note that study does not contribute significant variance leading us to conclude that it is adequate to combine samples.

Focal model	Compared to	No. of parameter	AIC	BIC	logLik	deviance	Chisq	Df	*p*
Full model: three random intercepts (Sample, Tech type, Participant ID)	--	5	21059	21091	-10524	21049			
Sample random intercept excluded	Full model	4	21057	21083	-10524	21049	0.00	1	.999
Technology type random intercept excluded	Full model	4	21052	21178	-10572	21144	95.68	1	**<0.001**
Participant ID random intercept excluded	Full model	4	22336	22362	-11164	22328	1279.68	1	**<0.001**

Note: Full model = intercept only model with intercept varying among Sample, Tech type, and Participant ID.

Table S10. Overview of model comparisons (Dependent variable: Ratings of manipulated attribute after treatment)

Model	No. of parameter	AIC	BIC	logLik	deviance		Df	*p*
Model 1	4	21057	21083	-10524	21049			
Model 2	5	19295	19327	-9642	19285	1763.95	1	**<0.001**
Model 3	7	19200	19245	-9593	19186	98.6689	2	**<0.001**
Model 4	8	18226	18278	-9105	18210	975.737	1	**<0.001**
Model 5	10	18200	18264	-9090	18180	30.4704	2	**<0.001**
Model 6	13	18202	18286	-9088	18176	4.04583	3	0.257

Table S11. Results of linear mixed-effects regression as part of manipulation verification. (Dependent variable: Change in the manipulated attribute)

	Model 1				**Model 2**				**Model 3**			
Predictors	***B***	***S.E.***	***CI***	***p***	***B***	***S.E.***	***CI***	***p***	***B***	***S.E.***	***CI***	***p***
(Intercept)	-0.09	0.09	- 0.27 – 0.09	0.35	-0.09	0.07	-0.23 – 0.06	0.244	-0.8	0.07	-0.23 – 0.06	0.257
Pre-rating manipulated attribute (PMA)					-1.14	0.03	-1.19 – -1.08	**<0.001**	-1.14	0.03	-1.21 – -1.08	**<0.001**
Direction (High vs. Low)												
Attribute (Risk vs. Benefit)												
Direction × Attribute												
PMA ×Direction												
PMA × Attribute												
Attribute												
PMA ×Direction × Attribute												
Random Effects												
σ^2	3.33				2.23				1.9			
τ_{00}	2.33 $_{\text{ParticipantID}}$ 0.02 $_{\text{Tech\_type}}$				2.62 $_{\text{ParticipantID}}$ 0.01 $_{\text{Tech\_type}}$				5.65 $_{\text{ParticipantID}}$ 0.01 $_{\text{Tech\_type}}$			
τ_{11}									0.06 $_{\text{ParticipantID.PMA}}$			
ρ_{01}									-0.73 $_{\text{ParticipantID}}$			
ICC	0.41				0.54				0.75			
N	1552 $_{\text{ParticipantID}}$ 3 $_{\text{Tech\_type}}$				1552 $_{\text{ParticipantID}}$ 3 $_{\text{Tech\_type}}$				1552 $_{\text{ParticipantID}}$ 3 $_{\text{Tech\_type}}$			
Observations	4656				4656				4656			
Marginal R^2 / Conditional R^2	0.000 / 0.414				0.210 / 0.638				0.147 / 0.786			

Note: Variables were coded as follows—Direction: -0.5 = Low, +0.5= High; Attribute: -0.5 = Benefit, +0.5= Risk;

Table S12. Results of linear mixed-effects regression as part of manipulation verification. (Dependent variable: Change in the manipulated attribute)

	Model 4				**Model 5**				**Model 6**			
Predictors	***B***	***S.E.***	***CI***	***p***	***B***	***S.E.***	***CI***	***p***	***B***	***S.E.***	***CI***	***p***
(Intercept)	-0.09	0.06	-0.21 – 0.04	0.162	-0.09	0.06	-0.21 – 0.04	0.173	-0.09	0.06	-0.21 – 0.04	0.185
Pre-rating manipulated attribute (PMA)	-1.07	0.03	-1.13 – -1.01	**<0.001**	-1.09	0.03	-1.15 – -1.03	**<0.001**	-1.09	0.03	-1.15 – -1.03	**<0.001**
Direction (High vs. Low)	2.53	0.07	2.40 – 2.67	**<0.001**	2.54	0.07	2.40 – 2.67	**<0.001**	2.56	0.07	2.42 – 2.69	**<0.001**
Attribute (Risk vs. Benefit)					-0.27	0.07	-0.40 – -0.13	**<0.001**	-0.27	0.07	-0.40 – -0.13	**<0.001**
Direction × Attribute					0.53	0.13	0.27 – 0.80	**<0.001**	0.49	0.14	0.22 – 0.75	**<0.001**
PMA ×Direction									-0.10	0.06	-0.22 – 0.02	0.109
PMA × Attribute Attribute									0.01	0.06	-0.11 – 0.14	0.819
PMA ×Direction × Attribute									0.16	0.12	-0.08 – 0.40	0.199
Random Effects												
σ^2	1.91				1.91				1.91			
τ_{00}	3.68 $_{\text{ParticipantID}}$				3.62 $_{\text{ParticipantID}}$				3.63 $_{\text{ParticipantID}}$			
	0.01 $_{\text{Tech\_type}}$				0.01 $_{\text{Tech\_type}}$				0.01 $_{\text{Tech\_type}}$			
τ_{11}	0.06 $_{\text{ParticipantID.PMA}}$				0.06 $_{\text{ParticipantID.PMA}}$				0.06 $_{\text{ParticipantID.PMA}}$			
ρ_{01}	-0.85 $_{\text{ParticipantID}}$				-0.85 $_{\text{ParticipantID}}$				-0.85 $_{\text{ParticipantID}}$			
ICC	0.66				0.65				0.66			
N	1552 $_{\text{ParticipantID}}$				1552 $_{\text{ParticipantID}}$				1552 $_{\text{ParticipantID}}$			
	3 $_{\text{Tech\_type}}$				3 $_{\text{Tech\_type}}$				3 $_{\text{Tech\_type}}$			
Observations	4656				4656				4656			
Marginal R^2 / Conditional R^2	0.330 / 0.771				0.333 / 0.770				0.333 / 0.771			

Note: Variables were coded as follows—Direction: -0.5 = Low, +0.5= High; Attribute: -0.5 = Benefit, +0.5= Risk;

Table S13. Comparisons of intercept only models (Dependent variable: Change in manipulated attribute). Note that study does not contribute significant variance leading us to conclude that it is adequate to combine samples.

Focal model	Compared to	No. of parameter	AIC	BIC	logLik	deviance	Chisq	Df	*p*
Full model: three random intercepts (Sample, Tech type, Participant ID)	--	5	20588	20620	-10289	20578			
Sample random intercept excluded	Full model	4	20586	20611	-10289	20578	0.00	1	.999
Technology type random intercept excluded	Full model	4	20597	20623	-10295	20589	11.67	1	**<0.001**
Participant ID random intercept excluded	Full model	4	21300	21326	-10646	21292	714.80	1	**<0.001**

Note: Full model = intercept only model with intercept varying among Sample, Tech type, and Participant ID.

Table S14. Overview of model comparisons (Dependent variable: **Change in manipulated attribute**)

Model	No. of parameter	AIC	BIC	logLik	deviance		Df	*p*
Model 1	4	20585.5	20611.3	-10289	20577.5			
Model 2	5	19294.8	19327	-9642.4	19284.8	1292.72	1	**<0.001**
Model 3	7	19200.1	19245.2	-9593.1	19186.1	98.6689	2	**<0.001**
Model 4	8	18226.4	18277.9	-9105.2	18210.4	975.737	1	**<0.001**
Model 5	10	18199.9	18264.4	-9090	18179.9	30.4704	2	**<0.001**
Model 6	13	18201.9	18285.7	-9087.9	18175.9	4.04583	3	0.260

Table S15. Results of linear mixed-effects regression as part of additional Main analysis (DV= Ratings on non-manipulated attribute after treatment).

	Model 1				Model 2				Model 3			
Predictors	***B***	***S.E.***	***CI***	***p***	***B***	***S.E.***	***CI***	***p***	***B***	***S.E.***	***CI***	***p***
(Intercept)	5.89	0.26	5.38 – 6.39	**<0.001**	5.89	0.11	5.66 – 6.11	**<0.001**	5.88	0.11	5.66 – 6.10	**<0.001**
Pre-rating manipulated attribute (PMA)					-0.26	0.03	-0.32 – -0.20	**<0.001**	-0.25	0.03	-0.31 – -0.19	**<0.001**
Pre-rating non-manipulated attribute (PNMA)					1.50	0.03	1.44 – 1.56	**<0.001**	1.50	0.03	1.43 – 1.56	**<0.001**
Direction (High vs. Low)												
Attribute (Risk vs. Benefit)												
Direction × Attribute												
PNMA × Direction												
PNMA × Attribute												
PNMA × Direction × Attribute												
Random Effects												
σ^2	3.63				2.05				1.81			
τ_{00}	2.73 $_{\text{ParticipantID}}$				1.21 $_{\text{ParticipantID}}$				2.12 $_{\text{ParticipantID}}$			
	0.19 $_{\text{Tech\_type}}$				0.03 $_{\text{Tech\_type}}$				0.03 $_{\text{Tech\_type}}$			
τ_{11}									0.04 $_{\text{ParticipantID.PNMA}}$			
ρ_{01}									-0.66 $_{\text{ParticipantID}}$			
ICC	0.45				0.38				0.54			
N	1552 $_{\text{ParticipantID}}$				1552 $_{\text{ParticipantID}}$				1552 $_{\text{ParticipantID}}$			
	3 $_{\text{Tech\_type}}$				3 $_{\text{Tech\_type}}$				3 $_{\text{Tech\_type}}$			
Observations	4656				4656				4656			
Marginal R^2 / Conditional R^2	0.000 / 0.446				0.448 / 0.656				0.400 / 0.727			
AIC	21070.49				18164.69				18090.16			
log-Likelihood	-10531.24				-9076.35				-9037.08			

Note: Variables were coded as follows—Direction: -0.5 = Low, +0.5= High; Attribute: -0.5 = Benefit, +0.5= Risk;

Table S16. Results of linear mixed-effects regression as part of additional Main analysis (DV= Ratings on non-manipulated attribute after treatment).

	Model 4				Model 5			
Predictors	***B***	***S.E.***	***CI***	***p***	***B***	***S.E.***	***CI***	***p***
(Intercept)	5.88	0.11	5.66 – 6.09	**<0.001**	5.88	0.10	5.67 – 6.08	**<0.001**
Pre-rating manipulated attribute (PMA)	-0.25	0.03	-0.30 – -0.19	**<0.001**	-0.21	0.03	-0.27 – -0.15	**<0.001**
Pre-rating non-manipulated attribute (PNMA)	1.52	0.03	1.46 – 1.59	**<0.001**	1.51	0.03	1.45 – 1.58	**<0.001**
Direction (High vs. Low)	-1.14	0.06	-1.26 – -1.01	**<0.001**	-1.16	0.06	-1.28 – -1.04	**<0.001**
Attribute (Risk vs. Benefit)					0.57	0.06	0.45 – 0.69	**<0.001**
Direction × Attribute					-1.31	0.12	-1.54 – -1.07	**<0.001**
PNMA × Direction								
PNMA × Attribute								
PNMA × Direction × Attribute								
Random Effects								
σ^2	1.81				1.82			
τ_{00}	1.77 $_{\text{ParticipantID}}$				1.34 $_{\text{ParticipantID}}$			
	0.03 $_{\text{Tech\_type}}$				0.03 $_{\text{Tech\_type}}$			
τ_{11}	0.04 $_{\text{ParticipantID.\_PNMA}}$				0.04 $_{\text{ParticipantID.\_PNMA}}$			
ρ_{01}	-0.72 $_{\text{ParticipantID}}$				-0.72 $_{\text{ParticipantID}}$			
ICC	0.5				0.43			
N	1552 $_{\text{ParticipantID}}$				1552 $_{\text{ParticipantID}}$			
	3 $_{\text{Tech\_type}}$				3 $_{\text{Tech\_type}}$			
Observations	4656				4656			
Marginal R^2 / Conditional R^2	0.457 / 0.728				0.514 / 0.722			
AIC	17812.31				17632.24			
log-Likelihood	-8897.15				-8805.12			

Note: Variables were coded as follows—Direction: -0.5 = Low, +0.5= High; Attribute: -0.5 = Benefit, +0.5= Risk;

Table S17. Results of linear mixed-effects regression as part of additional Main analysis

Model 6 (DV: Post-rating non-manipulated attribute)				
Predictors	***B***	***S.E.***	***CI***	***p***
Intercept	5.89	0.1	5.70 – 6.08	**<0.001**
Pre-rating manipulated attribute	-0.21	0.03	-0.27 – -0.15	**<0.001**
Pre-rating non-manipulated attribute (NMA)	1.51	0.03	1.45 – 1.57	**<0.001**
Direction (High vs. Low)	-1.15	0.06	-1.27 – -1.03	**<0.001**
Attribute (Risk vs. Benefit)	0.55	0.06	0.43 – 0.67	**<0.001**
NMA × Direction	0.14	0.05	0.04 – 0.25	**0.008**
NMA × Attribute	-0.16	0.06	-0.27 – -0.05	**0.004**
Direction × Attribute	-1.34	0.12	-1.58 – -1.10	**<0.001**
NMA × Direction× Attribute	0.13	0.11	-0.08 – 0.35	0.221
Random Effects				
σ^2			1.82	
$\tau_{00\ \mathrm{ParticipantID}}$			1.27	
$\tau_{00\ \mathrm{Tech\_type}}$			0.03	
$\tau_{11\ \mathrm{ParticipantID\_PNMA}}$			0.04	
$\rho_{01\ \mathrm{ParticipantID}}$			-0.71	
ICC			0.42	
$N_{\mathrm{ParticipantID}}$			1552	
$N_{\mathrm{Tech\_type}}$			3	
Observations			4656	
Marginal R^2 / Conditional R^2			0.518 / 0.719	
AIC			17632.35	
log-Likelihood			-8802.18	

Note: Variables were coded as follows—Direction: -0.5 = Low, +0.5= High; Attribute: -0.5 = Benefit, +0.5= Risk;

Table S18. Comparisons of intercept only models (Dependent variable: Ratings on manipulated attribute after treatment). Note that study does not contribute significant variance leading us to conclude that it is adequate to combine samples.

Focal model	**Compared to**	**No. of parameter**	**AIC**	**BIC**	**logLik**	**deviance**	**Chisq**	**Df**	***p***
Full model: three random intercepts (Sample, Tech type, Participant ID)	--	5	21071	21104	- 10531	21061			
Sample random intercept excluded	Full model	4	21069	21095	- 10531	21061	0.00	1	.999
Technology type random intercept excluded	Full model	4	21216	21242	- 10604	21208	146.66	1	**<0.001**
Participant ID random intercept excluded	Full model	4	21847	21872	-10919	21839	777.26	1	**<0.001**

Note: Full model = intercept only model with intercept varying among Sample, Tech type, and Participant ID.

Table S19. Overview of model comparisons (Dependent variable: Ratings on manipulated attribute after treatment)

Model	**No. of parameter**	**AIC**	**BIC**	**logLik**	**deviance**		**Df**	***p***
Model 1	5	21071.40	21103.63	-10530.70	21061.40			
Model 2	6	18151.34	18190.01	-9069.67	18139.34	2922.06	1	**<0.001**
Model 3	8	18077.02	18128.58	-9030.51	18061.02	78.32	2	**<0.001**
Model 4	9	17795.34	17853.35	-8888.67	17777.34	283.68	1	**<0.001**
Model 5	11	17608.85	17679.75	-8793.42	17586.85	190.49	2	**<0.001**
Model 6	14	17598.34	17688.58	-8785.17	17570.34	16.51	3	**<0.001**

Table S20. Results of linear mixed-effects regression as part of main analysis (DV= Change in non-manipulated attribute).

	Model 1				Model 2				Model 3			
Predictors	***B***	***S.E.***	***CI***	***p***	***B***	***S.E.***	***CI***	***p***	***B***	***S.E.***	***CI***	***p***
Intercept	-0.26	0.05	-0.36 – -0.16	**<0.001**	-0.26	0.11	-0.48 – -0.04	**0.021**	-0.27	0.11	-0.49 – -0.05	**0.017**
Pre-rating manipulated attribute (PMA)					-0.26	0.03	-0.32 – -0.20	**<0.001**	-0.25	0.03	-0.31 – -0.19	**<0.001**
Pre-rating non-manipulated attribute (PNMA)					-0.96	0.03	-1.02 – -0.90	**<0.001**	-0.97	0.03	-1.03 – -0.90	**<0.001**
Direction (High vs. Low)												
Attribute (Risk vs. Benefit)												
PNMA × Direction												
PNMA × Attribute												
Direction × Attribute												
PNMA × Direction × Attribute												
Random Effects												
σ^2	2.8				2.05				1.81			
τ_{00}	0.93 ParticipantID				1.21 ParticipantID				2.12 ParticipantID			
	0.00 Tech_type				0.03 Tech_type				0.03 Tech_type			
τ_{11}									0.04 ParticipantID._PNMA			
ρ_{01}									-0.66 ParticipantID			
ICC	0.25				0.38				0.54			
N	1552 ParticipantID				1552 ParticipantID				1552 ParticipantID			
	3 Tech_type				3 Tech_type				3 Tech_type			
Observations	4656				4656				4656			
Marginal R^2 / Conditional R^2	0.000 / 0.249				0.189 / 0.495				0.164 / 0.619			
AIC	19088.34				18164.69				18090.16			
log-Likelihood	-9540.17				-9076.35				-9037.08			

Table S21. Results of linear mixed-effects regression as part of main analysis (DV= Change in non-manipulated attribute).

	Model 4				Model 5			
Predictors	***B***	***S.E.***	***CI***	***p***	***B***	***S.E.***	***CI***	***p***
Intercept	-0.27	0.11	-0.48 – -0.06	**0.012**	-0.27	0.10	-0.47 – -0.07	**0.008**
Pre-rating manipulated attribute (PMA)	-0.25	0.03	-0.30 – -0.19	**<0.001**	-0.21	0.03	-0.27 – -0.15	**<0.001**
Pre-rating non-manipulated attribute (PNMA)	-0.94	0.03	-1.00 – -0.88	**<0.001**	-0.95	0.03	-1.01 – -0.89	**<0.001**
Direction (High vs. Low)	-1.14	0.06	-1.26 – -1.01	**<0.001**	-1.16	0.06	-1.28 – -1.04	**<0.001**
Attribute (Risk vs. Benefit)					0.57	0.06	0.45 – 0.69	**<0.001**
PNMA × Direction					-1.31	0.12	-1.54 – -1.07	**<0.001**
PNMA × Attribute								
Direction × Attribute								
PNMA × Direction × Attribute								
Random Effects								
σ^2	1.81				1.82			
τ_{00}	1.77 $_{\text{ParticipantID}}$				1.34 $_{\text{ParticipantID}}$			
	0.03 $_{\text{Tech\_type}}$				0.03 $_{\text{Tech\_type}}$			
τ_{11}	0.04 $_{\text{ParticipantID.\_PNMA}}$				0.04 $_{\text{ParticipantID.\_PNMA}}$			
ρ_{01}	-0.72 $_{\text{ParticipantID}}$				-0.72 $_{\text{ParticipantID}}$			
ICC	0.5				0.43			
N	1552 $_{\text{ParticipantID}}$				1552 $_{\text{ParticipantID}}$			
	3 $_{\text{Tech\_type}}$				3 $_{\text{Tech\_type}}$			
Observations	4656				4656			
Marginal R^2 / Conditional R^2	0.226 / 0.613				0.274 / 0.585			
AIC	17812.31				17632.24			
log-Likelihood	-8897.15				-8805.12			

Note: Variables were coded as follows—Direction: -0.5 = Low, +0.5= High; Attribute: -0.5 = Benefit, +0.5= Risk;

Table S22. Results of linear mixed-effects regression as part of the main analysis (DV= Change in non-manipulated attribute).

Model 6 (DV: Change in non-manipulated attribute)				
Predictors	***B***	***S.E.***	***CI***	***p***
Intercept	-0.26	0.10	-0.45 – -0.06	**0.009**
Pre-rating manipulated attribute (PMA)	-0.21	0.03	-0.27 – -0.15	**<0.001**
Pre-rating non-manipulated attribute (PNMA)	-0.95	0.03	-1.01 – -0.89	**<0.001**
Direction (High vs. Low)	-1.15	0.06	-1.27 – -1.03	**<0.001**
Attribute (Risk vs. Benefit)	0.55	0.06	0.43 – 0.67	**<0.001**
PNMA × Direction	0.14	0.05	0.04 – 0.25	**0.008**
PNMA × Attribute	-0.16	0.06	-0.27 – -0.05	**0.004**
Direction × Attribute	-1.34	0.12	-1.58 – -1.10	**<0.001**
PNMA × Direction× Attribute	0.13	0.11	-0.08 – 0.35	0.221
Random Effects				
σ^2			1.82	
$\tau_{00\ \mathrm{ParticipantID}}$			1.27	
$\tau_{00\ \mathrm{Tech\_type}}$			0.03	
$\tau_{11\ \mathrm{ParticipantID.PNMA}}$			0.04	
$\rho_{01\ \mathrm{ParticipantID}}$			-0.71	
ICC			0.42	
$N_{\mathrm{ParticipantID}}$			1552	
$N_{\mathrm{Tech\_type}}$			3	
Observations			4656	
Marginal R^2 / Conditional R^2			0.275 / 0.577	
AIC			17632.35	
log-Likelihood			-8802.18	

Note: Variables were coded as follows—Direction: -0.5 = Low, +0.5= High; Attribute: -0.5 = Benefit, +0.5= Risk;

Table S23. Comparisons of intercept only models (Dependent variable: Change in non-manipulated attribute). Note that study does not contribute significant variance leading us to conclude that it is adequate to combine samples.

Focal model	Compared to	No. of parameter	AIC	BIC	logLik	deviance	Chisq	Df	*p*
Full model: three random intercepts (Sample, Tech type, Participant ID)	--	5	19086	19118	- 9538	19076			
Sample random intercept excluded	Full model	4	19084	19110	- 9538	19076	0.00	1	1.00
Technology type random intercept excluded	Full model	4	19085	19111	- 9539	19077	1.32	1	0.249
Participant ID random intercept excluded	Full model	4	19344	19370	-9668	19336	259.96	1	**<0.001**

Note: Full model = intercept only model with intercept varying among Sample, Tech type, and Participant ID.

Table S24. Overview of model comparisons (Dependent variable: Change in non-manipulated attribute)

Model	No. of parameter	AIC	BIC	logLik	deviance		Df	*p*
Model 1	4	19084.1	19109.8	-9538	19076.1			
Model 2	6	18151.3	18190	-9069.7	18139.3	936.71	1	**<0.001**
Model 3	8	18077	18128.6	-9030.5	18061	78.32	2	**<0.001**
Model 4	9	17795.3	17853.4	-8888.7	17777.3	283.68	1	**<0.001**
Model 5	11	17608.9	17679.8	-8793.4	17586.9	190.49	2	**<0.001**
Model 6	14	17598.3	17688.6	-8785.2	17570.3	16.51	3	**<0.001**

Table S25. *Summary of results multilevel mediation model using the bmlm on High only subsample*

Parameter	Mean	SE	Median	2.5%	97.5%	n_eff	Rhat
a	1.15	0.06	1.15	1.05	1.26	19881	1
b	-0.46	0.02	-0.46	-0.50	-0.42	5730	1
cp	-0.27	0.05	-0.27	-0.37	-0.16	14980	1
me	-0.54	0.04	-0.54	-0.61	-0.47	10173	1
c	-0.81	0.06	-0.81	-0.92	-0.69	19453	1
pme	0.67	0.05	0.67	0.58	0.77	11093	1

Note. SE (for Standard Error) is the posterior standard deviation; *me* = magnitude of the mediation effect; *c* = total effect of IV on DV; *cp* = direct effect of IV on DV; *a* = IV on mediator; b = mediator on DV; *pme* = proportion of total effect that is mediated.

Table S26. *Summary of results multilevel mediation model using the bmlm on Low only subsample*

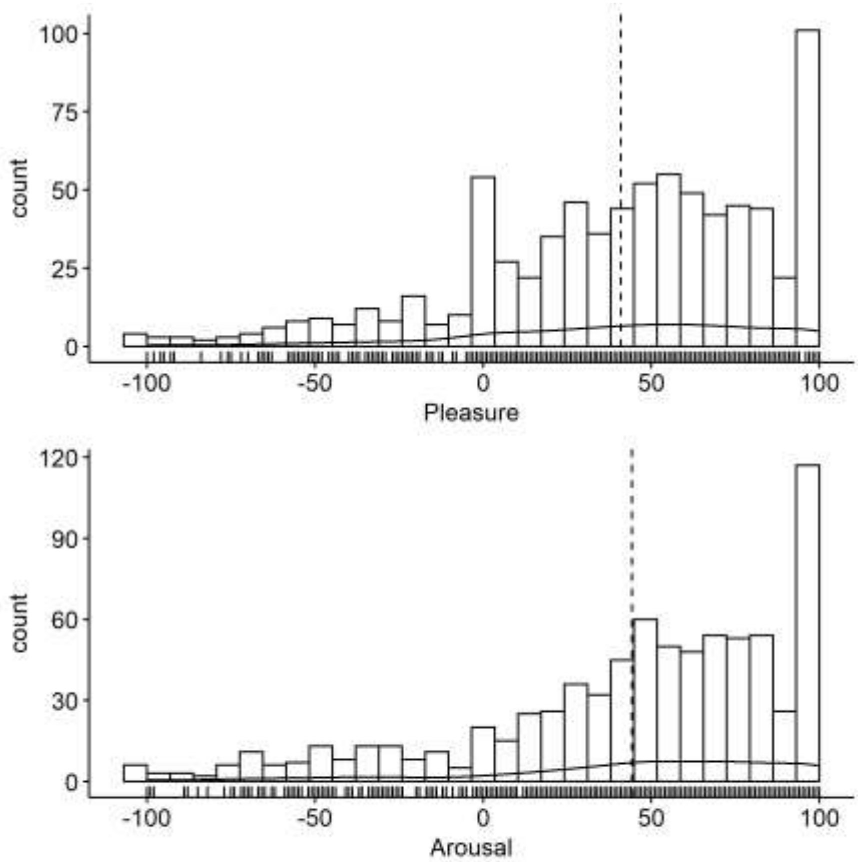
Parameter	Mean	SE	Median	2.5%	97.5%	n_eff	Rhat
a	-1.33	0.06	-1.33	-1.44	-1.22	17634	1
b	-0.42	0.02	-0.42	-0.45	-0.38	5096	1
cp	-0.25	0.05	-0.25	-0.35	-0.14	10448	1
me	0.55	0.04	0.55	0.48	0.62	8926	1
c	0.30	0.06	0.30	0.19	0.41	17632	1
pme	1.89	0.36	1.83	1.36	2.76	12377	1

Note. SE (for Standard Error) is the posterior standard deviation; *me* = magnitude of the mediation effect; *c* = total effect of IV on DV; *cp* = direct effect of IV on DV; *a* = IV on mediator; b = mediator on DV; *pme* = proportion of total effect that is mediated.

Table S27. *Descriptive statistics of variables measuring naturally occurring incidental mood Study 1 (Mturk sample)*

Variable	n	mean	sd	median	min	max	skew	kurtosis	se
Pleasure	776	41.03	44.57	48	-100	100	-0.79	0.34	1.60
Arousal	776	44.28	47.41	53	-100	100	-1.03	0.53	1.70

Figure S5. *Histogram and density plots of the responses to the measures of incidental mood.*



Note. The participants in the Mturk sample rated their current levels of: a) pleasure – *unpleasant* vs. *pleasant* and b) arousal – *deactivated* vs. *activated* (using two affective sliders that ranged from -100 to 100, centred in the middle)

Table S28. *Results of linear mixed-effects regression*. (Extension 1)

	DV: Pre-rating risks of the technology				
Predictors	***B***	***S.E***	***CI***	***p***	***df***
(Intercept)	5.45	0.45	4.56 – 6.33	**<0.001**	2320
Pre-rating manipulated attribute	0.53	0.05	0.44 – 0.63	**<0.001**	2320
Pleasure	0.07	0.08	-0.08 – 0.22	0.376	2320
Arousal	0.14	0.08	-0.02 – 0.29	0.080	2320
Pleasure × Arousal	0.00	0.05	-0.10 – 0.10	0.961	2320
Random Effects					
σ^2	4.26				
$\tau_{00\ \mathrm{ParticipantID}}$	1.51				
$\tau_{00\ \mathrm{Tech\_type}}$	0.6				
ICC	0.33				
$N_{\mathrm{ParticipantID}}$	776				
$N_{\mathrm{Tech\_type}}$	3				
Observations	2328				
Marginal R^2 / Conditional R^2	0.049 / 0.364				
AIC	10582.713				
log-Likelihood	-5283.356				

Table S29. *Results of linear mixed-effects regression*. (Extension 1)

	DV: Pre-rating benefits of technology				
Predictors	*B*	*S.E*	*CI*	*p*	*df*
(Intercept)	6.80	0.28	6.25 – 7.36	**<0.001**	2320
Pre-rating manipulated attribute (MP)	0.62	0.05	0.52 – 0.72	**<0.001**	2320
Pleasure	0.10	0.07	-0.05 – 0.24	0.194	2320
Arousal	0.03	0.08	-0.12 – 0.19	0.656	2320
Pleasure × Arousal	0.02	0.05	-0.08 – 0.11	0.743	2320
Random Effects					
σ^2			4		
$\tau_{00\ \mathrm{ParticipantID}}$			1.46		
$\tau_{00\ \mathrm{Tech\_type}}$			0.23		
ICC			0.30		
$N_{\mathrm{ParticipantID}}$			776		
$N_{\mathrm{Tech\_type}}$			3		
Observations			2328		
Marginal R^2 / Conditional R^2			0.065 / 0.343		
AIC			10443.55		
log-Likelihood			-5213.78		

Table S30. *Results of linear mixed-effects regression. (Extension: Naturally occurring incidental mood and the AH)*

	DV: Change in non-manipulated attribute			
Predictors	***B***	***S.E.***	***CI***	***p***
(Intercept)	-0.59	0.15	-0.88 – -0.29	**<0.001**
Pre-rating non-manipulated attribute	-0.63	0.05	-0.72 – -0.54	**<0.001**
Pre-rating manipulated attribute	-1.05	0.04	-1.13 – -0.97	**<0.001**
Pleasure	0.03	0.05	-0.07 – 0.13	0.557
Arousal	-0.06	0.05	-0.16 – 0.04	0.266
Change in manipulated attribute (CMA)	-0.70	0.05	-0.79 – -0.61	**<0.001**
Direction (High vs. Low)	0.30	0.09	0.13 – 0.48	**0.001**
Attribute (Risk vs. Benefit)	0.39	0.08	0.23 – 0.56	**<0.001**
Pleasure × Arousal	-0.02	0.03	-0.08 – 0.04	0.536
Pleasure × CMA	-0.09	0.04	-0.16 – -0.01	**0.025**
Arousal × CMA	0.05	0.04	-0.04 – 0.13	0.293
Pleasure × Arousal × CMA	-0.03	0.03	-0.09 – 0.02	0.201
Random Effects				
σ^2	1.88			
$\tau_{00\ \mathrm{ParticipantID}}$	0.62			
$\tau_{00\ \mathrm{Tech\_type}}$	0.05			
ICC	0.26			
$N_{\mathrm{ParticipantID}}$	776			
$N_{\mathrm{Tech\_type}}$	3			
Observations	2328			
Marginal R^2 / Conditional R^2	0.339 / 0.513			
AIC	8695.43			
log-Likelihood	-4332.72			

Table S31. *Results of linear mixed-effects regression (Extension 1: Risk/benefit strength)*

	DV: Change in non-manipulated attribute			
Predictors	***B***	***S.E.***	***CI***	***p***
(Intercept)	-0.26	0.12	-0.50 – -0.01	**0.039**
Pre-rating manipulated attribute (PMA)	-0.58	0.03	-0.64 – -0.52	**<0.001**
Pre-rating non-manipulated attribute (PNMA)	-1.01	0.03	-1.07 – -0.95	**<0.001**
Direction (High vs. Low)	-0.36	0.07	-0.49 – -0.23	**<0.001**
Manipulated Attribute (Risk vs. Benefit)	0.48	0.06	0.36 – 0.59	**<0.001**
Change in manipulated attribute (CMA)	-0.60	0.04	-0.68 – -0.52	**<0.001**
PNMA × Direction	0.15	0.05	0.05 – 0.25	**0.002**
PNMA × Manipulated Attribute	-0.10	0.05	-0.20 – -0.00	**0.049**
Direction × Manipulated Attribute	-0.91	0.13	-1.16 – -0.66	**<0.001**
Attribute × CMA	-0.27	0.05	-0.37 – -0.16	**<0.001**
PNMA × Direction × Manipulated Attribute	0.09	0.10	-0.10 – 0.29	0.356
Random Effects				
σ^2	1.7			
$\tau_{00\ \mathrm{ParticipantID}}$	0.75			
$\tau_{00\ \mathrm{Tech\_type}}$	0.04			
$\tau_{11\ \mathrm{ParticipantID.PNMA}}$	0.02			
$\rho_{01\ \mathrm{ParticipantID}}$	-0.62			
ICC	0.32			
$N_{\mathrm{ParticipantID}}$	1552			
$N_{\mathrm{Tech\_type}}$	3			
Observations	4656			
Marginal R^2 / Conditional R^2	0.372 / 0.572			
AIC	17103.895			
log-Likelihood	-8535.948			

Table S32. *Results of linear mixed-effects regression High only sub-sample of responses. (Extension: Risk/benefit strength)*

	DV: Change in non-manipulated attribute			
Predictors	***B***	***S.E.***	***CI***	***p***
(Intercept)	-0.84	0.18	-1.19 – -0.49	**<0.001**
Pre-rating manipulated attribute (PMA)	-0.71	0.05	-0.81 – -0.62	**<0.001**
Pre-rating non-manipulated attribute (PNMA)	-1.00	0.04	-1.08 – -0.92	**<0.001**
Attribute (Risk vs. Benefit)	-0.13	0.09	-0.30 – 0.04	0.133
Change in manipulated attribute (CMA)	-0.65	0.05	-0.76 – -0.55	**<0.001**
PNMA × Attribute	-0.06	0.07	-0.20 – 0.08	0.432
CMA × Attribute	-0.10	0.07	-0.23 – 0.03	0.130
Random Effects				
σ^2	1.74			
τ_{00} ParticipantID	0			
τ_{00} Tech_type	0.09			
τ_{11} ParticipantID.PNMA	0.02			
ρ_{01} ParticipantID	1			
ICC	0.05			
N ParticipantID	776			
N Tech_type	3			
Observations	2328			
Marginal R^2 / Conditional R^2	0.369 / 0.401			
AIC	8627.705			
log-Likelihood	-4301.852			

Note. Only responses from high Direction condition were part of the analysis

Table S33. *Results of linear mixed-effects regression with Low only sub-sample of responses. (Extension: Risk/benefit strength)*

	DV: Change in non-manipulated attribute			
Predictors	***B***	***S.E.***	***CI***	***p***
(Intercept)	0.32	0.08	0.16 – 0.48	**<0.001**
Pre-rating manipulated attribute	-0.46	0.04	-0.54 – -0.38	**<0.001**
Pre-rating non-manipulated attribute (PNMA)	-1.00	0.04	-1.08 – -0.92	**<0.001**
Attribute (Risk vs. Benefit)	1.10	0.08	0.95 – 1.25	**<0.001**
Change in manipulated attribute (CMA)	-0.40	0.05	-0.49 – -0.31	**<0.001**
PNMA × Attribute	-0.15	0.07	-0.28 – -0.01	**0.039**
CMA × Attribute	-0.30	0.06	-0.42 – -0.17	**<0.001**
Random Effects				
σ^2	1.7			
$\tau_{00\ \text{ParticipantID}}$	1.28			
$\tau_{00\ \text{Tech\_type}}$	0.01			
$\tau_{11\ \text{ParticipantID.PNMA}}$	0.02			
$\rho_{01\ \text{ParticipantID}}$	-0.83			
ICC	0.43			
$N_{\text{ParticipantID}}$	776			
$N_{\text{Tech\_type}}$	3			
Observations	2328			
Marginal R^2 / Conditional R^2	0.288 / 0.596			
AIC	8431.813			
log-Likelihood	-4203.907			

Note. Only responses from Low Direction condition were part of the analysis

Original article's results

We reproduced the results of the original study to help us accurately pinpoint the effect sizes for our own replication and to verify the degree of reproducibility.

Sample size before and after exclusions

The original study did mention exclusion criteria, but we did note a discrepancy related to the number of participants that was left unexplained in the original paper. The original study method stated that 213 undergraduate students were recruited in the experiment; whereas, data analysis section stated that there were 219 participants in the experiment. Therefore, this replication study took the numbers from the data analysed (219 participants) to ensure the integrity of the subsequent analysis.

T-tests

In the original experiment, the authors conducted paired-sample t-tests to compare the mean difference of perceived benefit and risk ratings before and after reading the affective information. However, the original authors only reported the results for the *Low Risk - Nuclear Power* condition with the exact number. Nevertheless, the results for all the conditions were presented on a plot in the original paper (Exhibit 6 in the original paper). Therefore, we decided to infer the t-values from the plot using an online tool called WebPlotDigitizer: https://automeris.io/WebPlotDigitizer/index.html for the estimation (Marin, Rohatgi, & Charlot, 2017). The p-values were calculated based on the estimated t-values. See Table S34 and S35, for the t-statistics and Cohen's d_z (with 95% CIs) of the manipulated and non-manipulated attributes, respectively. These statistics were used in our power analysis.

Table S34. The reported t-statistics of the change in judgments for manipulated attributes in the original paper

Condition		Manipulated Attribute	
		t-statistics	Cohen's d_z with 95% CIs
High Benefit[1]	Nuclear Power	$t(55) = 1.74$, p=.087	0.23[-0.03, 0.50]
	Natural Gas	$t(55) = 2.30$, p=.025*	0.31[0.04, 0.58]
	Food Preservatives	$t(55) = 4.96$, p<.001*	0.67[0.38, 0.96]
Low Benefit[1]	Nuclear Power	$t(55) = -2.48$, p=.016*[&3]	-0.34[-0.62, -0.07]
	Natural Gas	$t(55) = -3.91$, p<.001*	-0.54[-0.83, -0.25]
	Food Preservatives	$t(55) = -1.58$, p=.120	-0.22[-0.49, 0.05]
High Risk[2]	Nuclear Power	$t(52) = 0.82$, p=.416	0.11[-0.15, 0.37]
	Natural Gas	$t(52) = 8.35$, p<.001*	1.13[0.79, 1.46]
	Food Preservatives	$t(52) = 2.16$, p=0.035*	0.29[0.02, 0.56]
Low Risk[2]	Nuclear Power	$t(53) = -2.54$, p<.01*	-0.35[-0.62, -0.07]
	Natural Gas	$t(53) = -4.78$, p<.001*	-0.66[-0.95, -0.36]
	Food Preservatives	$t(53) = -3.97$, p<.001*	-0.55[-0.83, -0.26]

[1] In the high and low benefit conditions, the manipulated attribute was benefit and the non-manipulated attribute was risk

[2] In the high and low risk conditions, the manipulated attribute was risk and the non-manipulated attribute was benefit

[3] The direction of change was not in line with the hypothesis

* The result was significant

Table S35. The reported t-statistics of the change in judgements for non-manipulated attributes in the original paper

Condition		Non-manipulated Attribute	
		t-statistics	Cohen's d_z with 95% CIs
High Benefit[1]	Nuclear Power	$t(55) = -2.21$, p=.031*	-0.30[-0.56, -0.03]
	Natural Gas	$t(55) = -1.93$, p=.058	-0.26[-0.53, 0.01]
	Food Preservatives	$t(55) = -1.80$, p=.077	-0.24[-0.51, 0.02]
Low Benefit[1]	Nuclear Power	$t(55) = -1.94$, p=.057[3]	-0.27[-0.54, 0.01]
	Natural Gas	$t(55) = 0.42$, p=.676	0.06[-0.21, 0.33]
	Food Preservatives	$t(55) = -0.92$, p=.362	-0.13[-0.40, 0.14]
High Risk[2]	Nuclear Power	$t(52) = -0.60$, p=.551	-0.08[-0.34, 0.18]
	Natural Gas	$t(52) = -2.77$, p=.008*	-0.37[-0.64, -0.10]
	Food Preservatives	$t(52) = -1.81$, p=.076	-0.24[-0.51, 0.02]
Low Risk[2]	Nuclear Power	$t(53) = 3.33$, p<.01*	0.46[0.17, 0.74]
	Natural Gas	$t(53) = 3.09$, p=.003*	0.42[0.14, 0.70]
	Food Preservatives	$t(53) = 3.96$, p<.001*	0.54[0.26, 0.83]

[1] In the high and low benefit conditions, the manipulated attribute was benefit and the non-manipulated attribute was risk

[2] In the high and low risk conditions, the manipulated attribute was risk and the non-manipulated attribute was benefit

[3] The direction of change was not in line with the hypothesis

* The result was significant

Additional Analysis Mirroring original study results

Replication

Descriptive statistics of the measures across the two studies are noted in Table S39 and Table S40 of the supplementary material. To verify the effect of the manipulated attribute on the non-manipulated attribute, following the original experiment, we conducted paired samples *t*-tests (two-tailed). We contrasted people's judgments of risks and benefits for each particular technology before and after the implementation of the affective information (See Table S41–S44 in the supplementary material for detailed statistics). The findings show that, across both the MTurk and Prolific samples, the affective information did influence participants' judgments on perceived risks and benefits in the direction predicted by the AH. Specifically, this meant that increasing risks of a technology led to judgments of lower benefits while decreasing risks led to judgments of higher benefits. Vice versa, increasing benefits of a technology led to judgments of lower risks while decreasing benefits led to judgments of higher risks.

Similar to the original study, we then looked at the percentage of times the manipulation worked across both studies, i.e., when there was a directional change in the *manipulated* attribute which was consistent with the affective information (e.g., judgments of perceived risk decreased after receipt of information saying risk was low, etc.). As indicated in Table 36, in the MTurk sample, overall the manipulation worked in 53.2% of trials. The manipulation worked to a greater degree (63.1%) in the Prolific sample. Our results are similar to those obtained in the original experiment (there, the manipulation worked in 50% of the trials).

Table S36

Effect of the affective manipulation on the attribute that was manipulated across both studies, overall, and dependent on condition.

Study	Condition	Percent of trials that manipulation worked	Percent of trials that effect was opposite manipulation	Percent of trials no change
Study 1 (Mturk Sample)	High benefit	42.2	15.0	42.9
	Low benefit	53.1	15.0	31.9
	High risk	56.3	12.2	31.5
	Low risk	61.3	12.3	26.4
	Natural gas	53.6	15.1	31.3
	Nuclear power	51.8	12.0	36.2
	Food preservatives	54.1	13.8	32.1
	Overall (N = 2328 trials)	53.2	13.6	33.2
Study 2 (Prolific Sample)	High benefit	58.6	12.0	29.4
	Low benefit	63.8	11.1	25.2
	High risk	67.6	8.0	24.5
	Low risk	62.6	10.3	27.1
	Natural gas	64.6	12.4	23.1
	Nuclear power	59.7	8.1	32.2
	Food preservatives	65.1	10.6	24.4
	Overall (N = 2328 trials)	63.1	10.4	26.5

Note. A trial refers to one answer to a single scenario by a single participant. Given that there were three scenarios answered by 776 participants, in both studies, then the overall number of trials was 2328.

Subsequently, we also looked at the effect of the risk and benefit manipulation on the *non-manipulated* attribute (for details see Table S37). In the MTurk sample, of the 1238 trials in which the intended experimental manipulations worked, the effect on the non-manipulated attribute was congruent (as predicted), no change, and the opposite direction in 43.9%, 33.7%, and 22.5%, respectively. In the Prolific sample, of the 1469 trials in which the manipulations worked in the intended direction, the effect on the non-manipulated attribute was congruent, no change, and the opposite direction in 45.7%, 32.7%, 21.5%, of the cases respectively. These results echo those obtained in the original experiment where, of the trials in which the manipulations worked in the intended direction, the effect on the non-manipulated attribute was congruent, no change, and the opposite direction in 45%, 31%, 23%, of the cases respectively.

Finally, we tested the correlation between risk and benefits. The AH model predicts that the non-manipulated attribute would change in a direction that is affectively congruent with the manipulation. For example, if the manipulation was designed to decrease perceived benefit, then perceived risk should increase, etc., leading to an inverse relationship between the manipulated and non-manipulated attributes. Following the original study, we decided to correlate the twelve t values produced as results of the analysis on the impact of the manipulated on the non-manipulated attribute. There were twelve t values as a result of the combination of the four affective information and three technology scenarios. The sign of the t values indicated whether a change occurred in the predicted direction (e.g., judged benefits of nuclear power ought to increase after reading information on low risk producing a positive t value).We found strong support for a negative correlation: MTurk sample: $r(10) = -0.87$, 95% CI [-0.96, -0.59], $p = .003$; Prolific sample: $r(10) = -0.84$, 95% CI [-0.95, -0.50], $p < .001$ (see Table S38. Note that the correlation in the original study was -.74. As predicted, the non-manipulated attribute changed in the inverse direction that is affectively congruent with the manipulation. The results confirm the predictions of the AH and replicate the findings obtained in Finucane et al. (2000)'s Study 2.

Table S37. *Effect of the risk and benefit manipulations on judgments of the non-manipulated attribute.*

Study	Effect on the manipulated attribute	Effect on the non-manipulated attribute		
		Percent of trials that manipulation worked	Percent of trials that effect was opposite manipulation	Percent of trials no change
Study 1 (MTurk Sample)	Manipulation worked; N = 1238 (53.18 %)	43.9	22.5	33.7
	No change; N = 773 (33.20 %)	25.5	17.9	56.7
	Change was opposite; N =317 (13.62%)	30.3	36.0	33.8
	Total; N = 2328	35.9	22.8	41.3
Study 2 (Prolific Sample)	Manipulation worked; N = 1469 (63.1%)	45.7	21.5	32.7
	No change; N = 618 (26.5%)	28.8	16.5	54.7
	Change was opposite; N = 241 (10.4%)	29.9	33.6	36.5
	Total; N = 2328	39.6	21.4	39.0

Note. Trails refer to number of times the decision scenarios were answered— grouped under three different technology scenarios or experimental conditions; The table provides us with a summary of direction of changes in the non-manipulated attribute given the direction changes in the manipulated attributes.

Table S38

Comparison of the relationship between manipulated and non-manipulated attributes in the original study and our two replications.

Original study	Replication		Replication summary
-0.74 [-0.92, -0.30]	MTurk Sample	-0.87 [-0.96, -0.59]	Signal-consistent
	Prolific Sample	-0.84 [-0.95, -0.50]	Signal-consistent

Note. Pearson's correlation coefficient *(r)* with 95% confidence intervals

Table S39. Descriptive statistics of Study 1 (MTurk sample)

		Initial Assessment			Assessment after manipulation		
Scenario		*M*	*SD*	*Med*	*M*	*SD*	*Med*
High Benefit (n = 196)							
Food Preservatives	Benefit	6.44	2.46	7.00	7.33	2.39	8.00
	Risk	5.34	2.59	5.00	4.61	2.52	4.00
Natural Gas	Benefit	7.56	2.19	8.00	7.94	2.06	8.00
	Risk	4.80	2.55	5.00	4.66	2.45	5.00
Nuclear Power	Benefit	6.91	2.54	7.00	7.63	2.26	8.00
	Risk	6.37	2.76	7.00	5.71	2.78	6.00
Low Benefit (n = 191)							
Food Preservatives	Benefit	6.31	2.48	7.00	5.39	2.50	5.00
	Risk	5.11	2.29	5.00	4.90	2.30	5.00
Natural Gas	Benefit	7.31	2.13	8.00	6.12	2.42	6.00
	Risk	4.80	2.29	5.00	5.03	2.17	5.00
Nuclear Power	Benefit	6.61	2.66	7.00	5.53	2.70	5.00
	Risk	6.45	2.75	6.00	5.94	2.77	6.00
High Risk (n = 197)							
Food Preservatives	Benefit	6.31	2.45	7.00	5.30	2.59	5.00
	Risk	5.03	2.35	5.00	6.06	2.50	6.00
Natural Gas	Benefit	7.34	2.33	8.00	6.24	2.33	6.00
	Risk	4.71	2.46	5.00	6.40	2.36	7.00
Nuclear Power	Benefit	6.75	2.60	7.00	5.96	2.84	6.00
	Risk	6.26	2.67	6.00	7.08	2.72	8.00
Low Risk (n = 192)							
Food Preservatives	Benefit	6.39	2.41	7.00	7.17	2.25	7.00
	Risk	5.15	2.25	5.00	3.95	2.20	3.00
Natural Gas	Benefit	7.22	2.08	8.00	7.69	1.99	8.00
	Risk	4.84	2.23	5.00	3.97	2.25	4.00
Nuclear Power	Benefit	6.59	2.60	7.00	7.30	2.26	8.00
	Risk	6.49	2.50	7.00	4.91	2.47	5.00

Table S40. Descriptive statistics of Study 2 (Prolific sample)

		Initial Assessment			Assessment after manipulation		
Scenario		*M*	*SD*	*Med*	*M*	*SD*	*Med*
High Benefit (n = 195)							
Food Preservatives	Benefit	6.32	2.18	6.00	7.57	1.89	8.00
	Risk	4.97	2.13	5.00	4.28	2.13	4.00
Natural Gas	Benefit	7.12	1.87	7.00	7.96	1.72	8.00
	Risk	5.15	1.97	5.00	4.44	2.07	4.00
Nuclear Power	Benefit	6.45	2.31	7.00	7.75	1.95	8.00
	Risk	7.04	2.34	7.00	6.21	2.48	6.00
Low Benefit (n = 196)							
Food Preservatives	Benefit	6.60	2.09	7.00	5.16	2.11	5.00
	Risk	4.73	1.94	5.00	4.66	1.96	5.00
Natural Gas	Benefit	7.17	1.92	7.00	5.60	2.25	5.00
	Risk	5.07	1.95	5.00	5.23	1.80	5.00
Nuclear Power	Benefit	6.59	2.49	7.00	4.95	2.47	5.00
	Risk	7.30	2.16	8.00	6.81	2.22	7.00
High Risk (n = 188)							
Food Preservatives	Benefit	6.47	2.11	7.00	5.44	2.26	6.00
	Risk	4.94	2.08	5.00	6.65	2.13	7.00
Natural Gas	Benefit	6.84	2.11	7.00	5.56	2.19	5.00
	Risk	5.36	2.17	5.00	7.48	1.97	8.00
Nuclear Power	Benefit	6.60	2.16	7.00	5.70	2.62	6.00
	Risk	6.85	2.40	7.00	8.00	2.10	8.00
Low Risk (n = 197)							
Food Preservatives	Benefit	6.55	2.07	7.00	7.54	2.04	8.00
	Risk	4.99	2.12	5.00	3.67	2.06	3.00
Natural Gas	Benefit	6.88	2.07	7.00	7.64	1.89	8.00
	Risk	4.98	2.16	5.00	3.62	1.98	3.00
Nuclear Power	Benefit	6.48	2.41	7.00	7.21	2.21	8.00
	Risk	7.01	2.31	7.00	5.31	2.51	5.00

Table S41. Summary of paired-samples t-test results for Study 1 (Mturk Sample)

	Manipulated Attribute		Non-manipulated Attribute	
Condition	**t-stat**	**Cohen's d_z and CI**	**t-stat**	**Cohen's d_z and CI**
<u>High Benefit</u>				
Nuclear Power	t(195) = 5.01, *p* < .001	0.30 [0.18, 0.42]	t(195) = -4.98, *p* < .001	-0.24 [-0.34, -0.14]
Natural Gas	t(195) = 3.38, *p* = .001	0.18 [0.07, 0.28]	t(195) = -1.03, *p* = .306	-0.06 [-0.16, 0.05]
Food Preservatives	t(195) = 6.67, *p* < .001	0.37 [0.25, 0.48]	t(195) = -6.48, *p* < .001	-0.29 [-0.37, -0.20]
<u>Low Benefit</u>				
Nuclear Power	t(190) = -6.40, *p* < .001	-0.40 [-0.53, -0.27]	t(190) = -3.54, *p* = .001	-0.18 [-0.29, -0.08]
Natural Gas	t(190) = -8.35, *p* < .001	-0.52 [-0.65, -0.39]	t(190) = 1.84, *p* = .067	0.11 [-0.01, 0.22]
Food Preservatives	t(190) = -6.35, *p* < .001	-0.37 [-0.49, -0.25]	t(190) = -1.84, *p* = .067	-0.09 [-0.19, 0.01]
<u>High Risk</u>				
Nuclear Power	t(196) = 5.85, *p* < .001	0.30 [0.20, 0.41]	t(196) = -7.14, < .001	-0.29 [-0.37, -0.21]
Natural Gas	t(196) = 9.75, *p* < .001	0.70 [0.54, 0.86]	t(196) = -7.59, *p* < .001	-0.47 [-0.60, -0.34]
Food Preservatives	t(196) = 7.26, *p* < .001	0.42 [0.30, 0.54]	t(196) = -7.14, *p* < .001	-0.40 [-0.51, -0.29]
<u>Low Risk</u>				
Nuclear Power	t(191) = -10.29, *p* < .001	-0.64 [-0.77, -0.50]	t(191) = 5.35, *p* = < .001	0.29 [0.18, 0.39]
Natural Gas	t(191) = -6.44, *p* < .001	-0.39 [-0.51, -0.27]	t(191) =4.12, *p* < .001	0.23 [0.12, 0.34]
Food Preservatives	t(191) = -8.41, *p* < .001	-0.54 [-0.67, -0.40]	t(191) = 5.94, *p* < .001	0.33 [0.22, 0.45]

Table S42. Summary of paired sample t-test results for Study 2 (Prolific Sample)

	Manipulated Attribute		Non-manipulated Attribute	
Condition	**t-stat**	**Cohen's d_z and CI**	**t-stat**	**Cohen's d_z and CI**
High Benefit				
Nuclear Power	t(194) = 10.15, *p* < .001	0.60 [0.47, 0.73]	t(194) = -6.87, *p* < .001	-0.35 [-0.49, -0.21]
Natural Gas	t (194) = 7.19, *p* < .001	0.47 [0.33, 0.60]	t(194) = -4.99, *p* < .001	-0.35 [-0.49, -0.21]
Food Preservatives	t(194) = 8.78, *p* < .001	0.61 [0.46, 0.76]	t(194) = -6.19, *p* < .001	-0.33 [-0.43, -0.22]
Low Benefit				
Nuclear Power	t(195) = -9.97, *p* < .001	-0.66 [-0.81, -0.52]	t(195) = -4.18, *p* < .001	-0.23 [-0.33, -0.12]
Natural Gas	t(195) = -10.92, *p* < .001	-0.75 [-0.90, -0.59]	t(195) = 1.32, *p* = .188	0.09 [-0.04, 0.22]
Food Preservatives	t(195) = -9.82, *p* < .001	-0.69 [-0.84, -0.53]	t(195) = -0.61, *p* = .540	-0.04 [-0.15, 0.08]
High Risk				
Nuclear Power	t(187) = 9.34, *p* < .001	0.51 [0.39, 0.62]	t(187) = -6.06, *p* < .001	-0.37 [-0.49, -0.24]
Natural Gas	t(187) = 14.39, *p* < .001	1.02 [0.85, 1.19]	t(187) = -7.99, *p* < .001	-0.59 [-0.75, -0.43]
Food Preservatives	t(187) = 13.13, *p* < .001	0.82 [0.68, 0.96]	t(187) = -7.75, *p* < .001	-0.47 [-0.60, -0.34]
Low Risk				
Nuclear Power	t(196) = -11.45, *p* < .001	-0.70 [-0.84, -0.57]	t(196) = 5.62, *p* < .001	0.31 [0.20, 0.43]
Natural Gas	t(196) = -8.43, *p* < .001	-0.66 [-0.82, -0.49]	t(196) = 6.69, *p* < .001	0.38 [0.27, 0.50]
Food Preservatives	t(196) = -9.24, *p* < .001	-0.63 [-0.78, -0.49]	t(196) = 7.26, *p* < .001	0.48 [0.35, 0.62]

Table S43. Comparing MTurk sample replication and original findings

Condition	Manipulated Attribute			Non-manipulated Attribute		
	Original study	**Replication**	**Interpretation**	**Original study**	**Replication**	**Interpretation**
High Benefit						
Nuclear Power	0.23 [-0.03, 0.50]	0.30 [0.18, 0.42]	Signal- consistent	-0.30[-0.56, -0.03]	-0.24 [-0.34, -0.14]	Signal- consistent
Natural Gas	0.31[0.04, 0.58]	0.18 [0.07, 0.28]	Signal- inconsistent, weaker	-0.26[-0.53, 0.01]	-0.06 [-0.16, 0.05]	No signal- inconsistent
Food Preservatives	0.67 [0.38, 0.96]	0.37 [0.25, 0.48]	Signal- inconsistent, weaker	-0.24[-0.51, 0.02]	-0.29 [-0.37, -0.20]	Signal- consistent
Low Benefit[1]						
Nuclear Power	-0.34 [-0.62, -0.07]	-0.40 [-0.53, -0.27]	Signal- consistent	-0.27[-0.54, 0.01]	-0.18 [-0.29, -0.08]	Signal- consistent
Natural Gas	-0.54 [-0.83, -0.25]	-0.52 [-0.65, -0.39]	Signal- consistent	0.06[-0.21, 0.33]	0.11 [-0.01, 0.22]	No signal
Food Preservatives	-0.22 [-0.49, 0.05]	-0.37 [-0.49, -0.25]	Signal- consistent, stronger	-0.13[-0.40, 0.14]	-0.09 [-0.19, 0.01]	No signal
High Risk						
Nuclear Power	0.11 [-0.15, 0.37]	0.30 [0.20, 0.41]	Signal- consistent	-0.08[-0.34, 0.18]	-0.29 [-0.37, -0.21]	Signal- inconsistent, larger
Natural Gas	1.13[0.79, 1.46]	0.70 [0.54, 0.86]	Signal- inconsistent- weaker	-0.37[-0.64, -0.10]	-0.47 [-0.60, -0.34]	Signal- consistent
Food Preservatives	0.29 [0.02, 0.56]	0.42 [0.30, 0.54]	Signal- inconsistent- stronger	-0.24[-0.51, 0.02]	-0.40 [-0.51, -0.29]	Signal- inconsistent, larger
Low Risk						
Nuclear Power	-0.35 [-0.62,-0.07]	-0.64 [-0.77, -0.50]	Signal- inconsistent, stronger	0.46[0.17, 0.74]	0.29 [0.18, 0.39]	Signal- inconsistent, larger
Natural Gas	-0.66 [-0.95,-0.36]	-0.39 [-0.51, -0.27]	Signal- inconsistent, weaker	0.42[0.14, 0.70]	0.23 [0.12, 0.34]	Signal- inconsistent, weaker
Food Preservatives	-0.55 [-0.83, -0.26]	-0.54 [-0.67, -0.40]	Signal- consistent	0.54[0.26, 0.83]	0.33 [0.22, 0.45]	Signal- inconsistent, weaker

Table S44. Comparing Prolific sample replication and original findings

Condition	Manipulated Attribute			Non-manipulated Attribute		
	Original study	**Replication**	**Interpretation**	**Original study**	**Replication**	**Interpretation**
High Benefit						
Nuclear Power	0.23 [-0.03, 0.50]	0.60 [0.47, 0.73]	Signal- inconsistent, stronger	-0.30[-0.56, -0.03]	-0.35 [-0.45, -0.24]	Signal- consistent
Natural Gas	0.31[0.04, 0.58]	0.47 [0.33, 0.60]	Signal- inconsistent, stronger	-0.26[-0.53, 0.01]	-0.35 [-0.49, -0.21]	Signal- consistent
Food Preservatives	0.67 [0.38, 0.96]	0.61 [0.46, 0.76]	Signal- consistent	-0.24[-0.51, 0.02]	-0.33 [-0.43, -0.22]	Signal- consistent
Low Benefit[1]						
Nuclear Power	-0.34 [-0.62, -0.07]	-0.66 [-0.81, -0.52]	Signal- inconsistent, stronger	-0.27[-0.54, 0.01]	-0.23 [-0.33, -0.12]	Signal- consistent
Natural Gas	-0.54 [-0.83, -0.25]	-0.75 [-0.90, -0.59]	Signal- inconsistent, stronger	0.06[-0.21, 0.33]	0.09 [-0.04, 0.22]	No signal
Food Preservatives	-0.22 [-0.49, 0.05]	-0.69 [-0.84, -0.53]	Signal- inconsistent, stronger	-0.13[-0.40, 0.14]	-0.04 [-0.15, 0.08]	No signal
High Risk						
Nuclear Power	0.11 [-0.15, 0.37]	0.51 [0.39, 0.62]	Signal- inconsistent, stronger	-0.08[-0.34, 0.18]	-0.37 [-0.49, -0.24]	Signal- inconsistent, larger
Natural Gas	1.13[0.79, 1.46]	1.02 [0.85, 1.19]	Signal- consistent	-0.37[-0.64, -0.10]	-0.59 [-0.75, -0.43]	Signal- inconsistent, larger
Food Preservatives	0.29 [0.02, 0.56]	0.82 [0.68, 0.96]	Signal- inconsistent- stronger	-0.24[-0.51, 0.02]	-0.47 [-0.60, -0.34]	Signal- inconsistent, larger
Low Risk						
Nuclear Power	-0.35 [-0.62,-0.07]	-0.70 [-0.84, -0.57]	Signal- inconsistent, stronger	0.46[0.17, 0.74]	0.31 [0.2, 0.43]	Signal- inconsistent, weaker
Natural Gas	-0.66 [-0.95,-0.36]	-0.66 [-0.82, -0.49]	Signal- consistent	0.42[0.14, 0.70]	0.38 [0.27, 0.50]	Signal- consistent
Food Preservatives	-0.55 [-0.83, -0.26]	-0.63 [-0.78, -0.49]	Signal- consistent	0.54[0.26, 0.83]	0.48 [0.35, 0.62]	Signal- consistent

Framework for evaluation of the replications

Table S45. Criteria for evaluation of replications by LeBel et al. (2018). A classification of relative methodological similarity of a replication study to an original study. “Same” (“different”) indicates the design facet in question is the same (different) compared to an original study. IV = independent variable. DV = dependent variable. “Everything controllable” indicates design facets over which a researcher has control. Procedural details involve minor experimental particulars (e.g., task instruction wording, font, font size, etc.).

Target similarity	Highly similar				Highly dissimilar
Category	Direct replication				Conceptual replication
Design facet	**Exact replication**	**Very close replication**	**Close replication**	**Far replication**	**Very far replication**
Effect/ Hypothesis	Same/similar	Same/similar	Same/similar	Same/similar	Same/similar
IV operationalization	Same/similar	Same/similar	Same/similar	Different	Different
DV operationalization	Same/similar	Same/similar	Same/similar	Different	Different
IV stimuli	Same/similar	Same/similar	Different	Different	
DV stimuli	Same/similar	Same/similar	Different		
Procedural details	Same/similar	Different			
Physical setting	Same/similar	Different			
Contextual variables	Different				

Figure S6. Criteria for evaluation of replications by LeBel et al. (2019). A taxonomy for comparing replication effects to target article original findings.

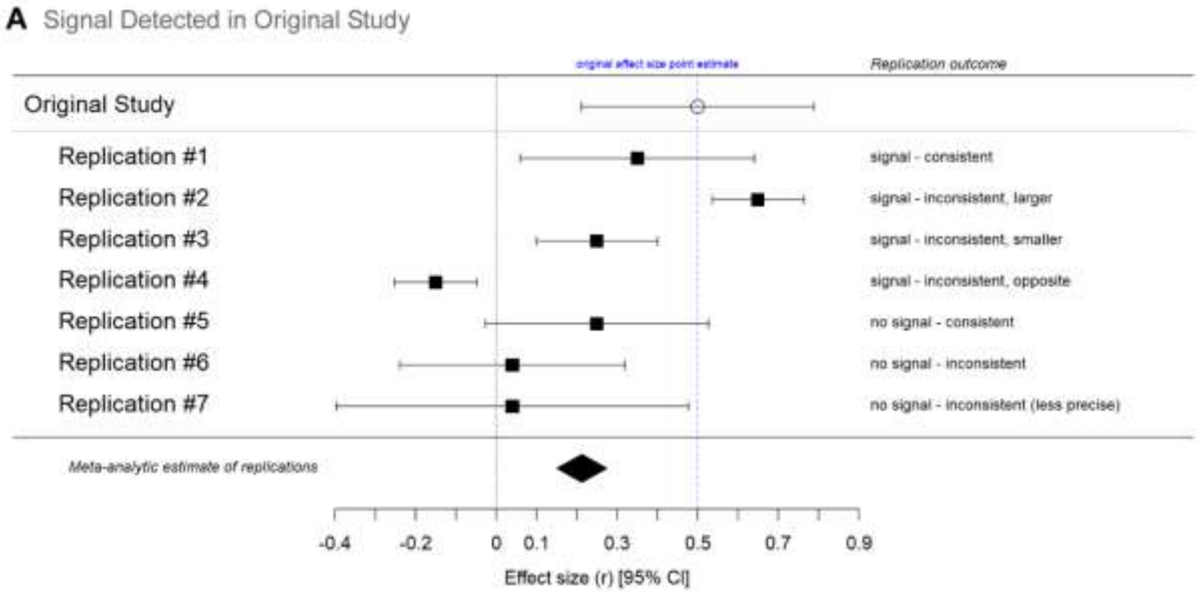


Table S46. Results of linear mixed-effects regression as part of manipulation verification. (Dependent variable: Ratings on manipulated attribute after treatment)

DV: Ratings of manipulated attribute				
Predictors	***Estimates***	***std. Error***	***CI***	***p***
(Intercept)	6.05	0.07	5.91 – 6.20	**<0.001**
Pre-rating manipulated attribute (PMA)	1.37	0.03	1.31 – 1.43	**<0.001**
Attribute (Risk vs. Benefit)	2.56	0.07	2.42 – 2.69	**<0.001**
Direction (High vs. Low)	-0.27	0.07	-0.40 – -0.13	**<0.001**
Sample (Mturk vs. Prolific)	0.06	0.07	-0.07 – 0.19	0.387
PMA ×Attribute	-0.1	0.06	-0.22 – 0.02	0.112
PMA ×Direction	0.01	0.06	-0.11 – 0.14	0.839
Direction × Attribute	0.49	0.14	0.22 – 0.76	**<0.001**
PMA ×Direction × Attribute	0.16	0.12	-0.09 – 0.40	0.205
Random Effects				
σ^2		1.91		
$\tau_{00\ \mathrm{ParticipantID}}$		3.61		
$\tau_{00\ \mathrm{Tech\_type}}$		0.01		
$\tau_{11\ \mathrm{ParticipantID.PreMV}}$		0.06		
$\rho_{01\ \mathrm{ParticipantID}}$		-0.85		
ICC		0.65		
$N_{\mathrm{ParticipantID}}$		1552		
$N_{\mathrm{Tech\_type}}$		3		
Observations		4656		
Marginal R^2 / Conditional R^2		0.395 / 0.791		
AIC		18234.584		
log-Likelihood		-9103.292		

Table S47. Results of linear mixed-effects regression as part of manipulation verification. (Dependent variable: Change in manipulated attribute)

DV: Change in manipulated attribute				
Predictors	***Estimates***	***std. Error***	***CI***	***p***
(Intercept)	-0.12	0.07	-0.26 – 0.03	**0.114**
Pre-rating manipulated attribute (PMA)	-1.09	0.03	-1.15 – -1.03	**<0.001**
Attribute (Risk vs. Benefit)	2.56	0.07	2.42 – 2.69	**<0.001**
Direction (High vs. Low)	-0.27	0.07	-0.40 – -0.13	**<0.001**
Sample (Mturk vs. Prolific)	0.06	0.07	-0.07 – 0.19	0.387
PMA ×Attribute	-0.1	0.06	-0.22 – 0.02	0.112
PMA ×Direction	0.01	0.06	-0.11 – 0.14	0.839
Direction × Attribute	0.49	0.14	0.22 – 0.76	**<0.001**
PMA ×Direction × Attribute	0.16	0.12	-0.09 – 0.40	0.205
Random Effects				
σ^2	1.91			
τ_{00} ParticipantID	3.61			
τ_{00} Tech_type	0.01			
τ_{11} ParticipantID.PreMV	0.06			
ρ_{01} ParticipantID	-0.85			
ICC	0.65			
N ParticipantID	1552			
N Tech_type	3			
Observations	4656			
Marginal R^2 / Conditional R^2	0.334 / 0.770			
AIC	18234.584			
log-Likelihood	-9103.292			

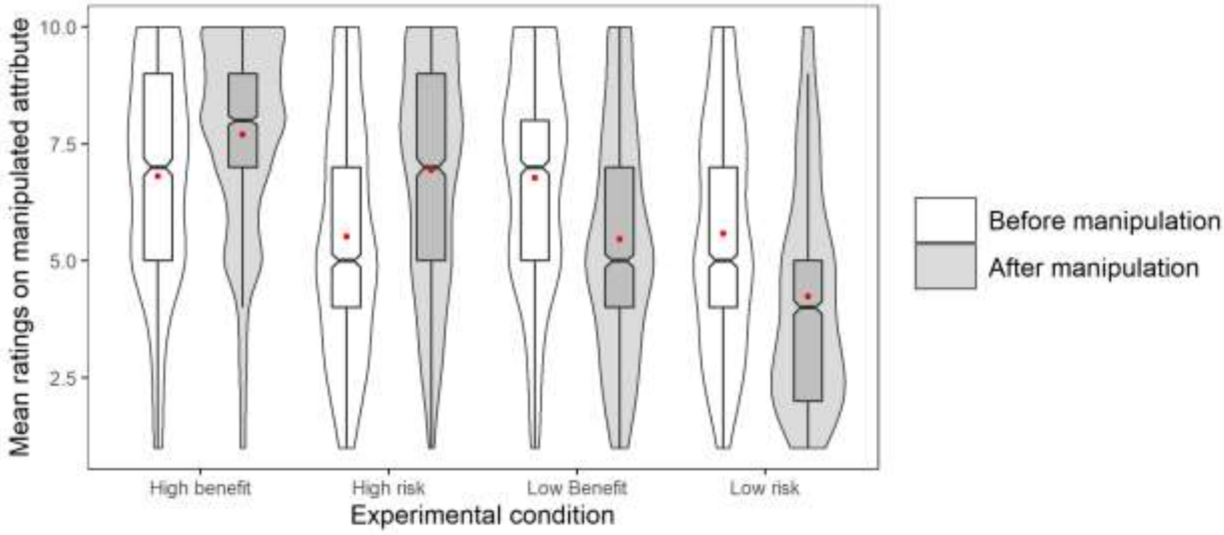
Table S48. Results of linear mixed-effects regression as part of manipulation verification. (Dependent variable: Post rating of non-manipulated attribute)

	Post treatment rating of non-manipulated variable			
Predictors	*Estimates*	*std. Error*	*CI*	*p*
Intercept	5.89	0.1	5.68 – 6.09	**<0.001**
Pre-rating manipulated attribute	-0.21	0.03	-0.27 – -0.15	**<0.001**
Pre-rating non-manipulated attribute (NMA)	1.51	0.03	1.45 – 1.57	**<0.001**
Direction (High vs. Low)	-1.15	0.06	-1.27 – -1.03	**<0.001**
Attribute (Risk vs. Benefit)	0.55	0.06	0.43 – 0.67	**<0.001**
Sample (Mturk vs. Prolific)	0.01	0.06	-0.11 – 0.12	0.924
NMA × Direction	0.14	0.05	0.04 – 0.25	**0.008**
NMA × Attribute	-0.16	0.06	-0.27 – -0.05	**0.004**
Direction × Attribute	-1.34	0.12	-1.58 – -1.10	**<0.001**
NMA × Direction× Attribute	0.13	0.11	-0.08 – 0.35	0.221
Random Effects				
σ^2	1.82			
τ_{00} ParticipantID	1.27			
τ_{00} Tech_type	0.03			
τ_{11} ParticipantID.PreNonMV	0.04			
ρ_{01} ParticipantID	-0.71			
ICC	0.42			
N ParticipantID	1552			
N Tech_type	3			
Observations	4656			
Marginal R^2 / Conditional R^2	0.518 / 0.719			
AIC	17638.119			
log-Likelihood	-8804.059			

Table S49. Results of linear mixed-effects regression as part of manipulation verification. (Dependent variable: Change non-manipulated attribute)

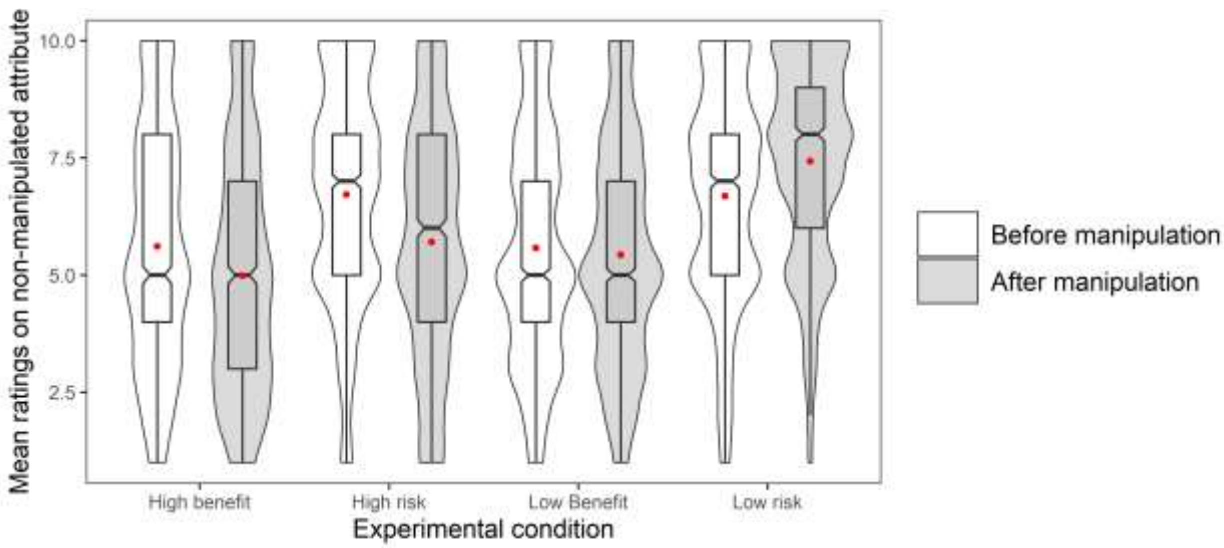
	Change Non Man V			
Predictors	*Estimates*	*std. Error*	*CI*	*p*
Intercept	-0.26	0.1	-0.46 – -0.06	**0.012**
Pre-rating manipulated attribute	-0.21	0.03	-0.27 – -0.15	**<0.001**
Pre-rating non-manipulated attribute (NMA)	-0.95	0.03	-1.01 – -0.89	**<0.001**
Direction (High vs. Low)	-1.15	0.06	-1.27 – -1.03	**<0.001**
Attribute (Risk vs. Benefit)	0.55	0.06	0.43 – 0.67	**<0.001**
Sample (Mturk vs. Prolific)	0.01	0.06	-0.11 – 0.12	0.924
NMA × Direction	0.14	0.05	0.04 – 0.25	**0.008**
NMA × Attribute	-0.16	0.06	-0.27 – -0.05	**0.004**
Direction × Attribute	-1.34	0.12	-1.58 – -1.10	**<0.001**
NMA × Direction× Attribute	0.13	0.11	-0.08 – 0.35	0.221
Random Effects				
σ^2	1.82			
$\tau_{00\ \text{ParticipantID}}$	1.27			
$\tau_{00\ \text{Tech\_type}}$	0.03			
$\tau_{11\ \text{ParticipantID.PreNonMV}}$	0.04			
$\rho_{01\ \text{ParticipantID}}$	-0.71			
ICC	0.42			
$N_{\text{ParticipantID}}$	1552			
$N_{\text{Tech\_type}}$	3			
Observations	4656			
Marginal R^2 / Conditional R^2	0.275 / 0.577			
AIC	17638.119			
log-Likelihood	-8804.059			

Figure S7. *Distribution of both pre- and after manipulation ratings on manipulated attribute as DV by experimental condition.*



Note. Figure includes violin plot displaying distribution of responses, boxplot displaying the median, first, and third quartiles, while the mean value is identified by the red circle.

Figure S8. *Distribution of both before- and after-manipulation ratings on non-manipulated attribute as DV by experimental condition.*



Note. Figure includes violin plot displaying distribution of responses, boxplot displaying the median, first, and third quartiles, while the mean value is identified by the red circle.

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Appendix A

Results of within-subjects mediation for High-Only responses using MEORE SPSS Macro

```
Run MATRIX procedure:

******************** MEMORE Procedure for SPSS Version 2.1 ***********************

                    Written by Amanda Montoya

               Documentation available at akmontoya.com

**************************************************************************

Model:
  1

Variables:
Y = PreNMV   PostNMV
M = PreMV    PostMV

Computed Variables:
Ydiff =       PreNMV    -      PostNMV
Mdiff =       PreMV     -      PostMV
Mavg = (      PreMV     +      PostMV   )      /2      Centered

Sample Size:
  2328

**************************************************************************
Outcome: Ydiff =  PreNMV    -      PostNMV

Model
      Effect       SE         t         p      LLCI      ULCI
'X'    .8196     .0388   21.1300     .0000     .7435     .8956

Degrees of freedom for all regression coefficient estimates:
  2327

**************************************************************************
Outcome: Mdiff =  PreMV     -      PostMV

Model
      Effect       SE         t         p      LLCI      ULCI
'X'   -1.1542    .0407  -28.3716     .0000   -1.2340   -1.0744

Degrees of freedom for all regression coefficient estimates:
  2327

**************************************************************************
Outcome: Ydiff =  PreNMV    -      PostNMV

Model Summary
        R      R-sq       MSE         F       df1       df2         p
     .3300     .1089    3.1238  142.0283    2.0000 2325.0000     .0000
```

Model

	coeff	SE	t	p	LLCI	ULCI
'X'	.4552	.0426	10.6928	.0000	.3717	.5387
Mdiff	-.3157	.0188	-16.7969	.0000	-.3525	-.2788
Mavg	.0568	.0170	3.3358	.0009	.0234	.0903

Degrees of freedom for all regression coefficient estimates:
2325

************************** TOTAL, DIRECT, AND INDIRECT EFFECTS **************************

Total effect of X on Y

Effect	SE	t	df	p	LLCI	ULCI
.8196	.0388	21.1300	2327.0000	.0000	.7435	.8956

Direct effect of X on Y

Effect	SE	t	df	p	LLCI	ULCI
.4552	.0426	10.6928	2325.0000	.0000	.3717	.5387

Indirect Effect of X on Y through M

	Effect	BootSE	BootLLCI	BootULCI
Ind1	.3644	.0347	.2972	.4325

Indirect Key
Ind1 'X' -> Mdiff -> Ydiff

******************************** ANALYSIS NOTES AND WARNINGS
****

Bootstrap confidence interval method used: Percentile bootstrap.

Number of bootstrap samples for bootstrap confidence intervals:
5000

The following variables were mean centered prior to analysis:
(PreMV + PostMV) /2

Level of confidence for all confidence intervals in output:
95.00

------ END MATRIX -----

Appendix B

Results of within-subjects mediation for Low-Only responses using MEORE SPSS Macro

Run MATRIX procedure:

```
******************** MEMORE Procedure for SPSS Version 2.1 **********************

                    Written by Amanda Montoya

               Documentation available at akmontoya.com

**********************************************************************************

Model:
  1

Variables:
Y = PreNMV   PostNMV
M = PreMV    PostMV

Computed Variables:
Ydiff =        PreNMV    -      PostNMV
Mdiff =        PreMV     -      PostMV
Mavg = (       PreMV     +      PostMV   )      /2      Centered

Sample Size:
  2328

**********************************************************************************
Outcome: Ydiff =  PreNMV    -      PostNMV

Model
      Effect       SE        t        p      LLCI      ULCI
'X'   -.2990     .0378   -7.9105    .0000    -.3731    -.2249

Degrees of freedom for all regression coefficient estimates:
  2327

**********************************************************************************
Outcome: Mdiff =  PreMV    -      PostMV

Model
      Effect       SE        t        p      LLCI      ULCI
'X'   1.3269     .0436   30.4388    .0000    1.2414    1.4124

Degrees of freedom for all regression coefficient estimates:
  2327

**********************************************************************************
Outcome: Ydiff =  PreNMV    -      PostNMV

Model Summary
        R      R-sq      MSE         F       df1       df2         p
     .2677     .0717    3.0897   89.7299    2.0000  2325.0000     .0000
```

Model

	coeff	SE	t	p	LLCI	ULCI
'X'	.0004	.0431	.0085	.9933	-.0841	.0848
Mdiff	-.2256	.0173	-13.0209	.0000	-.2596	-.1916
Mavg	.0497	.0164	3.0230	.0025	.0174	.0819

Degrees of freedom for all regression coefficient estimates:
2325

************************* TOTAL, DIRECT, AND INDIRECT EFFECTS *************************

Total effect of X on Y

Effect	SE	t	df	p	LLCI	ULCI
-.2990	.0378	-7.9105	2327.0000	.0000	-.3731	-.2249

Direct effect of X on Y

Effect	SE	t	df	p	LLCI	ULCI
.0004	.0431	.0085	2325.0000	.9933	-.0841	.0848

Indirect Effect of X on Y through M

	Effect	BootSE	BootLLCI	BootULCI
Ind1	-.2993	.0329	-.3628	-.2346

Indirect Key
Ind1 'X' -> Mdiff -> Ydiff

****************************** ANALYSIS NOTES AND WARNINGS
****

Bootstrap confidence interval method used: Percentile bootstrap.

Number of bootstrap samples for bootstrap confidence intervals:
5000

The following variables were mean centered prior to analysis:
(PreMV + PostMV) /2

Level of confidence for all confidence intervals in output:
95.00

------ END MATRIX -----