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Is the Effect of Trust on Risk Perceptions a Matter of Knowledge, Control, and Time? An Extension and Direct-Replication Attempt of Siegrist and Cvetkovich (2000)

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Abstract

The complexity of societal risks such as pandemics, artificial intelligence, and climate change may lead laypeople to rely on experts and authorities when evaluating these threats. While Siegrist and Cvetkovich showed that competence-based trust in authorities correlates with perceived societal risks and benefits only when people feel unknowledgeable, recent research has yielded mixed support for this foundational work. To address this discrepancy, we conducted a direct-replication study (preregistered; 1,070 participants, 33 risks, 35,310 observations). The results contradict the original findings. However, additional non-preregistered analyses indicate an alternative perspective aligning with compensatory control theory and the description-experience framework: experiences with insufficient personal control over a threat may amplify individuals' dependency on powerful others for risk mitigation. These findings highlight the need to reevaluate how trust shapes risk perceptions. Recent societal and technological shifts might have heightened the desire for control compared to subjective knowledge in why people resort to trust.

Keywords

trust, risk, personal control, subjective knowledge, experiential learning

People encounter a growing number of risks throughout their lives, ranging from daily threats like road traffic to catastrophic incidents such as pandemics and environmental disasters. Given the uncertainty and complexity surrounding these societal risks, laypeople may derive risk evaluations from heuristics, particularly by drawing on trustworthy opinions from and expectations about people and organizations (Earle & Cvetkovich, 1995; Freudenburg, 1993; Norris, 2022; Siegrist, 2021). Moreover, the likelihood and societal consequences of hazards often depend on powerful decision-makers who steer risk management, with one notable example being the pivotal position of governments in mitigating and adapting to climate change-related disasters (Intergovernmental Panel on Climate Change, 2014; Mazzucato, 2021). This dependency of risk perceptions on trust plays a vital role in inciting societal stability and change (Brick et al., 2021; Siegrist, 2021; Slovic, 1993). For instance, trust in experts and decision-makers 5 months before the Fukushima nuclear accident predicted subsequent public risk responses (Visschers & Siegrist, 2013), and trust fueled extensive behavioral change during the COVID-19 pandemic (Chambon et al., 2022; Siegrist & Bearth, 2021).

Trust refers to a tendency to "accept vulnerability based upon positive expectations of the intentions or behaviors of another" (Rousseau et al., 1998, p. 395). Based on this notion of trust as a means to reduce uncertainty in forming beliefs and actions, Siegrist and Cvetkovich (2000) showed that competence-based trust in authorities correlates with

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perceptions of societal risks and benefits of hazards only when people experience a knowledge deficit. This foundational work proposed that feeling unknowledgeable about a risk prompts compensatory reliance on heuristic cues, such that laypeople may form risk and benefit perceptions by relying on accessible information like beliefs about trustworthy others and their opinions (Earle et al., 2010; Siegrist, 2021; Siegrist & Cvetkovich, 2000). An example for this assertion is that individuals may perceive trustworthy labels as helpful information in evaluating the efficiency of an unfamiliar type of FFP2 face mask. Extensions of the model suggest that morality-based trust attributions (such as regarding a person's benevolence) play a more important role in the trust-knowledge interaction compared to competence-based trust attributions (like confidence in a person's ability), albeit with marginal statistical differences due to the strong correlation between these trust facets in risk responses (Earle et al., 2010; Earle & Siegrist, 2008; Siegrist, 2021). Altogether, the literature suggests that subjective knowledge moderates the effect of trust in predicting risk and benefit perceptions across trust attributions.

Recent research found mixed evidence on the interaction between subjective knowledge and trust in conceptual replications of Siegrist and Cvetkovich (2000)'s influential model. Three studies by See (2009) conceptually replicated the trust-knowledge interaction effect on policy support as an outcome in the contexts of study loans and environmental pollution. Similarly, Sailer et al. (2022) observed the interaction effect on self-reported compliance with COVID-19 safety measures. Other research examined the interplay of trust and knowledge perceptions in response to societal threats without testing for an interaction effect and by shedding light on mechanisms such as information processing (e.g., Holland & Cortina, 2017; Katsuya, 2002; Miller et al., 2016; Shepherd & Kay, 2012).

In contrast, studies examining COVID-19 safety behavior obtained mixed evidence for the interaction between trust and knowledge (Granados Samayoa et al., 2021; Zhu et al., 2022), while studies on COVID-related panic behavior (Sailer et al., 2022) and judgments of governmental performance (Thomson & Brandenburg, 2019) yielded nonsignificant interaction effects. Likewise, Pauer, Rutjens, and van Harreveld (2022) failed to obtain evidence for the interaction in three studies in the domains of COVID-19, meat consumption, and climate change. Notably, these authors found an alternative moderation by personal control over a risk. More specifically, trust in authorities (but not in the industry or consumers) predicted risk evaluations only in people who experienced a lack of personal control over outcomes, which is in line with compensatory control theory (Kay et al., 2009; Landau et al., 2015). That is, individuals often depend on powerful others to manage a threat, and relying on them affords individuals to regain a sense of structure and predictability to compensate for a lack of personal control (Ma et al., 2023; Rutjens et al., 2010).

One potential explanation for these mixed findings is cross-temporal changes in the phenomenon reported by Siegrist and Cvetkovich (2000) due to societal shifts (Muthukrishna et al., 2021). Their data were collected before the widespread availability of information through the internet and the growing public awareness of the climate crisis, along with the current populist and anti-democratic surges in right-wing ideologies (Norris & Inglehart, 2019). Although the current study does not aim to investigate the impact of specific societal shifts, such changes might have altered the relationship between trust attributions and subjective knowledge in predicting perceived risk. For example, the public's direct access to recordings of police brutality on the internet could diminish the perceived dependence on secondhand information or generic trust attributions.

Moreover, publication bias and false-positive results may contribute to the mixed findings, as many studies that probe interaction effects are underpowered (Sommet et al., 2023). The sample in the original study by Siegrist and Cvetkovich (2000) consisted of 90 students. Crucially, however, they utilized 25 risk domains, whereas later conceptual replication attempts of the trust-knowledge interaction (e.g., Pauer, Rutjens, & van Harreveld, 2022; See, 2009) employed only a single risk domain per study. This discrepancy could possibly give rise to mixed findings due to domain-specific boundary conditions and other motivational drivers of the trust-risk association than subjective knowledge. The current study therefore attempted a direct replication of the original study.

Exploratory Extension Attempts

In addition to the direct-replication attempt, our study extended the original study by examining (a) a conceptually related moderation by personal control and (b) potential boundary conditions. As our preregistration described these extension attempts only vaguely, they should not be treated as confirmatory but exploratory.

Given that each of the conceptual replication studies of the trust-knowledge interaction only employed a single risk domain, one could argue that previous failed conceptual replications (e.g., Sailer et al., 2022) might have emerged in a subgroup of domains where subjective knowledge is less relevant than other conceptually related variables, like personal control, in determining the effect of trust on perceived risk. By the same token, however, those variables could have confounded the trust-knowledge interaction Siegrist and Cvetkovich (2000) reported across 25 risk domains (Pauer, Rutjens, & van Harreveld, 2022). For instance, the desires for knowledge and personal control are distinct but intertwined: Knowledge deficits can lead to feeling a loss of control, and conversely, a desire to gain control can drive the pursuit of knowledge (Antonovsky, 1996; Landau et al., 2015; Shepherd & Kay, 2012; Whitson et al., 2022). These considerations underscore the importance of exploring a broader set of factors in the trust-risk association.

The impact of subjective knowledge and variables such as personal control on whether people draw on trust attributions in evaluating risk varies across different risk domains (Earle & Siegrist, 2008). Earle and Siegrist (2008) argued that individuals who feel an aversive lack of knowledge are more likely to rely on trust attributions when evaluating societal risks that they perceive as personally relevant, such as pesticides. For risks that appear more distant, like asteroid impacts, the interaction between trust and knowledge might be still relevant, albeit to a smaller extent; this attenuation is presumably due to the increased difficulty that individuals face in accessing domain-relevant information about trustworthy others (Earle & Siegrist, 2008). Our study therefore included exploratory analyses of possible boundary conditions of the trust-knowledge interaction, focusing on two prominent themes from the risk literature: psychological distance to a risk (Keller et al., 2022; McDonald et al., 2015; Trope & Liberman, 2010) and whether people learn about a risk through descriptive information or experiential exposure (Hertwig & Wulff, 2022; Slovic, 1987; Weber, 2006). We explored their potential roles in explaining why previous studies yielded mixed findings on the interaction between trust and subjective knowledge in risk perceptions.

One possibility could be, for example, that the need for gaining knowledge about a risk is more central to domains that require descriptive learning, like nuclear power, whereas experiential exposure to a risk could give precedence to the motivational consequences of personal control in moderating the trust-risk association, such as in bicycling (e.g., McDonald et al., 2015). This exemplifies one possibility of how the roles of subjective knowledge and personal control in the trust-risk association could differ by the mode through which people learn about a risk (i.e., descriptive and experiential learning). However, both descriptive and experiential learning about a risk domain may decrease its perceived distance (Keller et al., 2022; McDonald et al., 2015; Trope & Liberman, 2010), and psychological distance to a risk could reflect another boundary condition of the interaction between trust and subjective knowledge (Earle & Siegrist, 2008). Our study presents non-confirmatory analyses of these possible boundary conditions, which were not reported in our preregistration. To this extent, the study explores whether boundary conditions account for the mixed findings in previous literature on the interaction between trust and subjective knowledge.

Overview of the Current Study

Preregistered Replication Attempt

We conducted a close direct replication of Siegrist and Cvetkovich (2000)'s finding of an interaction effect between subjective knowledge and competence-based trust in authorities on perceived societal risks and benefits. These authors reported a stronger negative (positive) correlation between trust and risk (benefit) perceptions the less knowledgeable people felt about a risk domain. Given mixed findings from recent research (e.g., Pauer, Rutjens, & van Harreveld, 2022; See, 2009), a replication of the original findings would bolster a fundamental assumption about risk perception and the epistemic value of trust.

Non-Preregistered Extensions

A non-replication, however, would necessitate more comprehensive insights into why trust predicts risk perceptions. For this reason, our study includes a second set of non-preregistered analyses, which we therefore treat as non-confirmatory. First, exploratory tests examined whether the mixed findings from previous research emerged due to boundary conditions of the moderating effect of knowledge across risk domains. Second, given that the original study measured solely competence-based trust in authorities, we also explored the role of benevolence-based trust in Siegrist and Cvetkovich (2000)'s model. Third, we explored a possible moderation by personal control as an alternative model, in line with our preregistered "plan to investigate the conditions under which either knowledge or control moderate the effect on risk perceptions." Overall, our non-confirmatory extension attempts aimed at substantiating and qualifying *why* people derive risk evaluations from trust.

We report all measures, sample size decisions, and exclusions. The data, preregistration, questionnaire, R code, and Supplemental File are openly accessible on OSF: https://osf.io/gn9vp/?view_only=f4b3cfa9efa448f6a2cb863ad359e13a.

Method

Sample

As outlined in the preregistration, we retained a final sample of 1,070 participants (65.3% identified as female, 33.6% male, 1.1% selected "none of the above") with a mean age of 26.6 (SD = 11.0). Each participant completed 33 repeated measurements, resulting in 35,310 observations. The sample included 446 Prolific workers from the United States (41.7%), and students from three university subject pools in Germany and the Netherlands.

We determined the target sample based on feasibility given the complexity of power simulations for multilevel analysis, and therefore exceeded the recommended number of observations many times (Gabriel et al., 2019). Following the preregistered procedures, students completed the survey up until May 25, 2022, and after this date, we recruited workers from Prolific to reach 1,070 participants. Eventually, 1,256 people completed the questionnaire, and the remaining 115 people who

Table 1. *List of Items Measured in the Present Study, Each Anchored by 33 Risk Domains With Separate Response Scales*

Items from the original study (Siegrist & Cvetkovich, 2000) With 7-Point Response Scales	
Perceived risk	"In general, how risky do you consider each of the following items to be for your country of residence as a whole?" ranging from *not at all risky* to *very risky.*
Perceived benefit	"In general, how beneficial do you consider each of the following items to be for your country of residence as a whole?" ranging from *not at all beneficial* to *very beneficial.*
Subjective knowledge	"In general, how much do you know about the risks and benefits associated with the following items?" ranging from *know almost nothing* to *know a lot.*
Competence-based trust in authorities	"In general, how much confidence do you have in the authorities regulating the following items?" ranging from *no confidence at all* to *high confidence.*
Additional items	
Benevolence-based trust in authorities (Pauer, Rutjens, & van Harreveld, 2022)	"In general, to what extent do you think the authorities are motivated to prevent negative consequences of:" anchored by 7-point response scales ranging from *not at all* to *very much.*
Personal control perception (Armitage & Conner, 1999; Noordewier & Rutjens, 2021; Pauer, Rutjens, & van Harreveld, 2022):	"How much personal control do you feel you have over the risks and benefits of the following issues for your life?" The 7-point response scales followed the 33 risk domains and ranged from 1—*much less than I would like* to 4—*just the right amount* and 7—*much more than I would like.*
Experiential exposure and descriptive learning (Hertwig et al., 2004, 2022; Pauer, Rutjens, & van Harreveld, 2023; Weber, 2006)	"How frequently do you *personally encounter*:" and "How frequently do you *receive information* related to the risks/safety of the following issues? This includes information from, for example, the news, movies, and personal communication." Both items were anchored by response scales ranging from 1—*very infrequently* to 7—*very frequently.*
Psychological distance (Većkalov et al., 2022)	"Some concepts can feel distant, while others can feel close to ourselves and our lives. In that regard, how close or distant do the following issues feel to you?", the response scales ranged from 1—*very close to me* to 7—*very distant from me.*

dropped out before completing it (8.4%) were not included in any analyses as preregistered. We excluded 186 participants (14.8%) who failed at least one of two simple attention checks (e.g., "select strongly disagree") or responded to the questionnaire with a median speed per item below 0.75 seconds, as per the preregistered exclusion criteria.

Procedure and Analytic Strategy

Participants received payment or research credits for completing an online study on "attitudes related to different risks." They first provided informed consent and answered sociodemographic questions, that is, age, gender, education, and conservatism. The first block of four randomized variables assessed the original items on perceived risk, benefit, knowledge, and trust on separate pages (see Table 1). Each of the items anchored a list of 33 risk domains that were presented in randomized order. The 33 domains covered the 25 items from Siegrist and Cvetkovich (2000) who selected from a list employed by Alhakami and Slovic (1994). In addition to the 25 original items, we added eight items from the same list from Alhakami and Slovic (1994) and from the U.N. Human Development Report (United Nations Development Programme, 2020) to improve statistical power and construct space (see Figure 1). Afterward, a second randomized block assessed a total of five additional items for the same 33 risk domains. Overall, the study adhered to very close replication standards (see Table 2; LeBel et al., 2018).

Unless stated otherwise, we employed a multilevel framework using the lme4 package (Bates et al., 2014) in R and ancillary packages to account for subject- and domain-specific variance by nesting individual responses on level 1 variables in participants and risk domains (Brown, 2021; Hox, 2018). The level 1 predictors were person-mean centered in multilevel analyses (C. K. Enders & Tofighi, 2007). We did not include random slopes for which the variances were zero (Gabriel et al., 2019; Hoffman & Walters, 2022; Hox, 2018) and reported any exclusions of random slopes. We report standardized coefficients, calculated as described in Hox (2018), by multiplying the unstandardized coefficient and the standard deviation of the predictor, divided by the standard deviation of the outcome. As preregistered, alpha was .05. In our multilevel models, p-values were obtained using Satterthwaite-Approximation in lmerTest (Kuznetsova et al., 2017). In addition to our primary analyses, we ran non-preregistered robustness checks (a) to control for sociodemographic variables (at level 2 as they remain constant across risk domains for each participant) and (b) using the statistical approach and the subset of 25 risk domains from the original study, along with a corresponding multilevel model specification.

Results

We report (1) an interaction effect between competence-based trust in authorities and subjective knowledge on perceived societal risk and benefit across 33 domains within a

Table 2. *Replication Closeness Based on LeBel et al. (2018)*

Design facet	Replication	Deviation from the original study
IV construct	Same	*n/a*
DV construct	Same	*n/a*
IV operationalization	Same	Minor wording difference (i.e., "for your country of residence as a whole" instead of the original "for the United States society as a whole").
DV operationalization	Same	Minor wording difference (as above).
Population	Similar	The original study used U.S. introductory students. We sampled Dutch and German students and U.S. residents via Prolific.
Procedural details	Similar	We minimized order effects through randomization (the original study reduced order effects only through four conditions with different question orders).
Physical settings	Different	The replication study was run online and the original study was with paper and pencil.
Context	Different	The replication was conducted in 2022.
Overall replication classification	Very close replication	

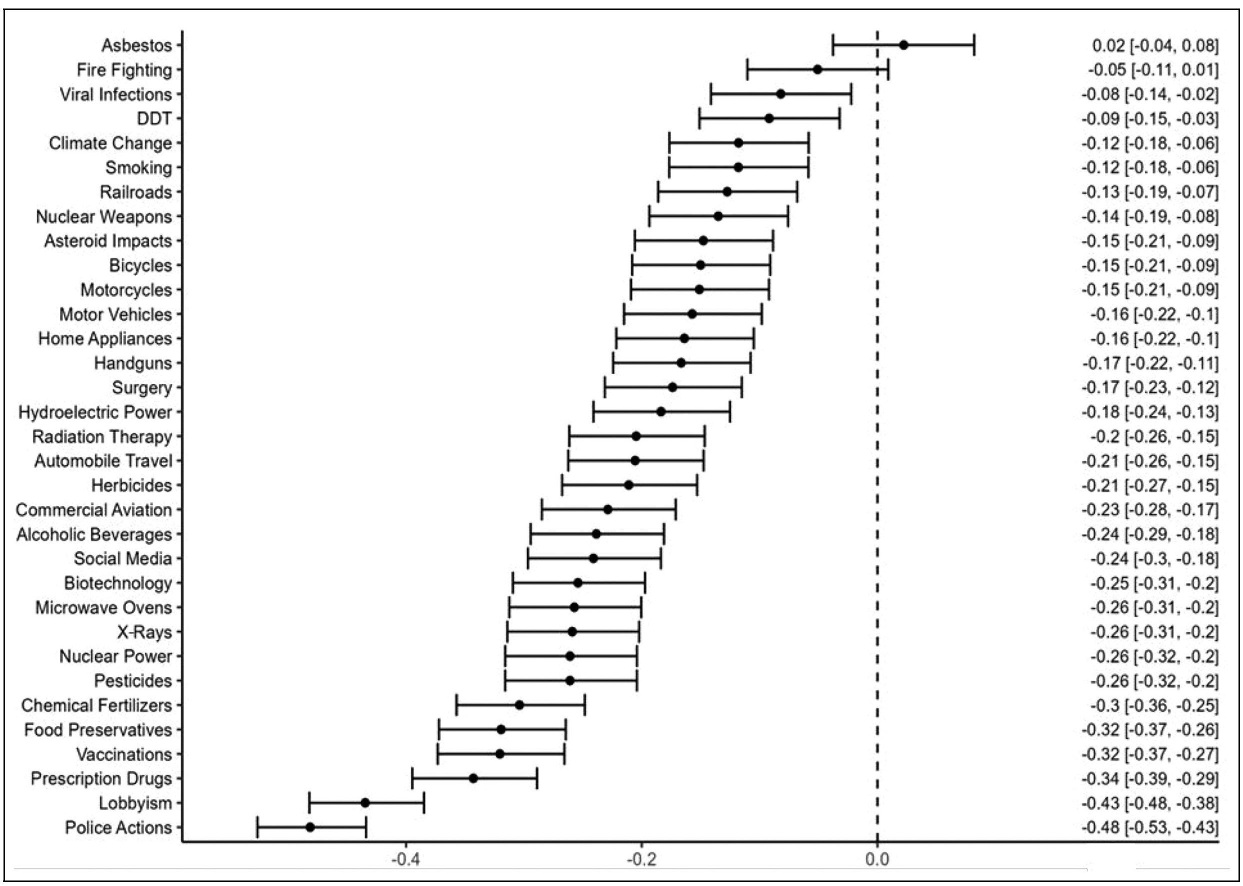

Figure 1. *Trust-Risk Correlation Coefficients by Domain with 95% Confidence*

multilevel framework, as preregistered, since it reflects the most informative and adequate statistical approach for nested data (Hox, 2018). The remainder of this section reports (2) non-preregistered replication tests and (3) exploratory extension attempts of the original study. This includes (3.1) tests of boundary conditions to investigate whether the original pattern of findings emerges in a systematic subset of risk domains. We also present (3.2) analyses of a conceptually related moderation of the trust-risk association by personal control, as well as (3.3) its boundary conditions.

Non-Preregistered Preliminary Analysis

To evaluate the value of multilevel modeling, we first calculated intraclass correlations and decomposed the sources of variability in perceived societal risk using a random intercept-only multilevel model (Hox, 2018; see Tables 3 and 4 for descriptive data). Participants and domains explained 15.9% and 29.4% of the variance in risk ratings, respectively. Lai and Kwok (2015) suggested that a multilevel framework is warranted if the design effect index (deff) exceeds 1.1 as an indicator of substantial variability by the cluster variables. This was confirmed in the case of participants and domains as cluster variables, deff = 6.1 and 315, respectively. For converging evidence, we compared the random effects model with a baseline model without random effects for participants or domains. Including the random effects resulted in significantly better model fit, $\chi^2(2) = 18{,}251$, $p < .001$. Therefore, the multilevel framework was warranted.

Competence-based trust in authorities was significantly associated with perceived risk (see Table 4), corroborating Siegrist and Cvetkovich (2000)'s replication of prior work (Freudenburg, 1993; Siegrist, 1999, 2021). There was considerable heterogeneity in the correlation coefficients as a function of risk domain (see Figure 1). This variability indicates a potential dependency of the trust-risk association on domain-specific features of a risk, which could moderate the trust-risk association.

Preregistered Replication Tests

We utilized a multilevel analysis for our replication attempt of Siegrist and Cvetkovich (2000)'s interaction model of subjective knowledge and competence-based trust in authorities predicting (1) risk and (2) benefit perceptions, as preregistered. First, the data revealed that the trust-risk association was significantly stronger at high compared to low levels of knowledge (see Table 5 and Figure 2), such that the interaction pattern was the opposite of the original study.

Second, we tested whether subjective knowledge interacted with competence-based trust to predict benefit perceptions. The interaction effect was nonsignificant, $\beta <$ .01, 95% CI [.00, .01], $p = .282$ (see Table 6). Notably, the trend of the effect was opposite to the original study, such that the simple slope of trust on perceived benefit was nonsignificantly smaller at low (compared to high) knowledge.

Exploratory Analyses

As the remainder reports non-preregistered analyses to further explore the interaction effects between trust and subjective knowledge and between trust and personal control, we treat these analyses as non-confirmatory.

Non-preregistered Replication Tests and Robustness Checks

Given that the sample of the current study is less homogeneous than the original sample of U.S. students, we explored whether the interaction effect between competence-based trust and subjective knowledge on perceived risk persisted when adding sociodemographic variables to the model (i.e., age, conservatism, education, gender, and U.S. residence). The trust-knowledge interaction term remained significant in this non-preregistered model, $\beta = -.01$, 95% CI [−.02; .00], $p = .005$. Moreover, the same pattern of findings resulted from robustness checks with higher replication closeness by using the 25 risk domains from the original study instead of 33 (see Supplemental Table S1), when discarding domain as a cluster variable (Supplemental Table S2), and in the original and non-multilevel correlation analyses employed by Siegrist and Cvetkovich (Supplemental Figure S1). Also, an alternative model exploring the interaction between benevolence-based trust and subjective knowledge on perceived risk revealed an inverse direction for the interaction effect, $\beta = -.02$, 95% CI [−.03; −.02], $p < .001$.

Likewise, when exploring perceived benefits as an outcome of the interaction between competence-based trust and subjective knowledge, the interaction effect remained inconsistent with the original study in multiple robustness checks, including (a) adding sociodemographic variables to the model (i.e., age, conservatism, education, gender, and U.S. residence; $\beta < .01$, 95% CI [−.01, .01], $p = .486$), (b) using the original number of 25 risk domains (see Supplemental Table S4), (c) discarding domain as a cluster variable (see Supplemental Table S5), and (d) employing the original correlation approach (see Supplemental Figure S1). Test (c) revealed a significant trust-knowledge interaction effect on perceived benefits, and its direction again contradicted Siegrist and Cvetkovich (2000). Similarly, when exploring an interaction effect between benevolence-based trust and subjective knowledge on perceived benefits, its direction significantly contradicted the original study, $\beta = .01$, 95% CI [.01; .02], $p = .008$. Overall, our non-preregistered analyses further corroborate a pattern opposite to the direction of the trust-knowledge interaction reported by Siegrist and Cvetkovich (2000).

Non-preregistered Boundary Conditions of the Moderation by Subjective Knowledge

While the present data revealed an absence of the original pattern of findings, the interaction effect between subjective knowledge and competence-based trust on perceived risk that Siegrist and Cvetkovich (2000) reported might still

Table 3. *Means of Key Variables Ranked Across 33 Risk Domains, With Dotted Lines Indicating the Grand Mean*

Perceived societal risk			Competence-based trust			Subjective knowledge			Personal control			Experiential learning		
Domain	*M*	*SD*	Domain	*M*	*SD*	Domain	*M*	*SD*	Domain	*M*	*SD*	Domain	*M*	*SD*
Climate Change	6.02	1.39	Fire Fighting	5.28	1.53	Smoking	5.77	1.21	Bicycles	4.09	1.14	Social Media	6.33	1.33
Nuclear Weapons	5.71	1.73	Surgery	5.11	1.56	Social Media	5.69	1.13	Alc. Beverages	4.04	1.36	Home Appliances	5.81	1.78
Smoking	5.53	1.44	Bicycles	4.95	1.73	Alc. Beverages	5.53	1.21	Smoking	3.89	1.47	Automobile Travel	5.69	1.57
Handguns	5.28	1.81	X-rays	4.86	1.60	Climate Change	5.45	1.22	Home Appliances	3.86	1.20	Microwave Ovens	5.54	1.79
Viral Infections	5.23	1.49	Railroads	4.82	1.56	Bicycles	5.30	1.47	Microwave Ovens	3.85	1.13	Bicycles	5.51	1.87
Asbestos	4.71	1.77	Vaccinations	4.79	1.71	Automobile Travel	5.09	1.39	Social Media	3.59	1.61	Motor Vehicles	5.41	1.82
Nuclear Power	4.57	1.91	Radiation Therapy	4.59	1.57	Vaccinations	5.09	1.37	Vaccinations	3.57	1.27	Alc. Beverages	5.04	1.86
Alc. Beverages	4.50	1.50	Home Appliances	4.58	1.73	Handguns	4.88	1.61	Automobile Travel	3.52	1.32	Climate Change	5.01	1.79
Lobbyism	4.43	1.65	Microwave Ovens	4.54	1.81	Motor Vehicles	4.79	1.52	Motor Vehicles	3.40	1.34	Vaccinations	4.81	1.58
Social Media	4.39	1.60	Automobile Travel	4.46	1.55	Police Actions	4.74	1.44	Motorcycles	3.36	1.30	Food Preservatives	4.70	1.85
Pesticides	4.35	1.51	Motor Vehicles	4.42	1.56	Viral Infections	4.71	1.48	Prescription Drugs	3.34	1.33	Railroads	4.44	2.03
Chem. Fertilizers	4.26	1.53	Hydroelec. Power	4.38	1.57	Prescription Drugs	4.65	1.50	Surgery	3.26	1.27	Smoking	4.19	2.15
Police Actions	4.21	1.64	Motorcycles	4.34	1.56	Surgery	4.55	1.51	X-Rays	3.24	1.24	Viral Infections	4.12	1.79
DDT	4.05	1.55	Com. Aviation	4.30	1.67	Motorcycles	4.39	1.59	Fire Fighting	3.17	1.25	Prescription Drugs	4.00	2.03
Motorcycles	4.04	1.64	Biotechnology	4.27	1.56	Nuclear Weapons	4.29	1.69	Railroads	3.15	1.26	Com. Aviation	3.47	1.84
Herbicides	3.99	1.46	Prescription Drugs	4.20	1.69	Fire Fighting	4.28	1.60	Radiation Therapy	3.07	1.26	Motorcycles	3.41	1.87
Motor Vehicles	3.93	1.55	Asbestos	4.12	1.67	Home Appliances	4.16	1.76	Com. Aviation	3.00	1.30	Police Actions	2.91	1.61
Asteroid Impacts	3.92	2.21	Nuclear Power	3.85	1.80	Nuclear Power	4.11	1.62	Food Preservatives	2.90	1.31	Pesticides	2.73	1.69
Automobile Travel	3.88	1.53	Food Preservatives	3.83	1.60	X-Rays	4.02	1.61	Hydroelec. Power	2.77	1.29	Herbicides	2.47	1.61
Prescription Drugs	3.74	1.61	Alc. Beverages	3.81	1.64	Railroads	4.01	1.61	Biotechnology	2.75	1.24	Chem. Fertilizers	2.47	1.62
Radiation Therapy	3.59	1.51	Viral Infections	3.77	1.66	Microwave Ovens	3.93	1.66	Asbestos	2.69	1.27	X-Rays	2.46	1.49
Food Preservatives	3.40	1.53	Handguns	3.69	1.98	Com. Aviation	3.82	1.71	DDT	2.65	1.26	Surgery	2.40	1.52
Fire Fighting	3.32	1.90	Police Actions	3.62	1.80	Food Preservatives	3.71	1.55	Herbicides	2.56	1.22	Biotechnology	2.32	1.55
Com. Aviation	3.27	1.47	DDT	3.61	1.47	Radiation Therapy	3.63	1.62	Handguns	2.50	1.41	Lobbyism	2.25	1.62
Surgery	3.20	1.57	Nuclear Weapons	3.59	1.86	Pesticides	3.62	1.56	Pesticides	2.49	1.19	Fire Fighting	2.23	1.46
Biotechnology	3.16	1.48	Herbicides	3.55	1.46	Asbestos	3.46	1.79	Chem. Fertilizers	2.47	1.20	Hydroelec. Power	2.11	1.43
X-Rays	2.94	1.47	Pesticides	3.54	1.53	Lobbyism	3.32	1.76	Viral Infections	2.43	1.31	Handguns	2.01	1.63
Railroads	2.56	1.36	Chem. Fertilizers	3.51	1.51	Chem. Fertilizers	3.18	1.53	Police Actions	2.30	1.25	Nuclear Power	1.89	1.43
Hydroelec. Power	2.52	1.35	Smoking	3.35	1.67	Biotechnology	3.15	1.60	Nuclear Power	2.10	1.22	DDT	1.75	1.27
Vaccinations	2.40	1.48	Asteroid Impacts	3.18	1.87	Hydroelec. Power	3.08	1.67	Lobbyism	2.10	1.24	Asbestos	1.74	1.25
Microwave Ovens	2.34	1.38	Social Media	2.77	1.48	Asteroid Impacts	3.00	1.73	Asteroid Impacts	2.03	1.33	Radiation Therapy	1.66	1.23
Home Appliances	2.31	1.30	Lobbyism	2.67	1.48	Herbicides	2.95	1.61	Climate Change	2.01	1.32	Nuclear Weapons	1.44	1.17
Bicycles	2.23	1.41	Climate Change	2.64	1.50	DDT	2.24	1.59	Nuclear Weapons	1.79	1.17	Asteroid Impacts	1.25	0.95

Note. Alc. Beverages = Alcoholic Beverages, Chem. Fertilizers = Chemical Fertilizers, Com. Aviation = Commercial Aviation, Hydroelec. Power = Hydroelectric Power.

Table 4. *Summary Statistics Including Means, Standard Deviations, and Pearson Correlations (N = 1,070)*

Variables	*M*	*SD*	1.	2.	3.	4.	5.	6.
1. Perceived risk	3.88	0.79						
2. Trust	4.03	1.00	–.22***					
3. Subjective knowledge	4.20	0.92	.20***	.06*				
4. Personal control	2.97	0.70	–.11***	.27***	.05			
5. Experience	3.44	0.67	.12***	.08**	.37***	.04		
6. Description	3.29	0.92	.14***	.09**	.33***	.11***	.54***	
7. Psych. Distance	4.14	0.81	–.12***	–.03	–.33***	–.05	–.58***	–.40***

Note. *$p < .05$. **$p < .01$. ***$p < .001$.

Table 5. *Multilevel Model Predicting Risk Perceptions From Trust, Subjective Knowledge, and Their Interaction Terms Across 33 Risk Domains*

Predictors	β	95% CI *LL*	95% CI *UL*	*p*
Trust	–.16	–.19	–.13	<.001
Knowledge	.09	.06	.13	<.001
Trust × knowledge	–.02	–.03	–.01	.003
Conditional effects of trust at				
−1 *SD* knowledge	–.15	–.18	–.11	<.001
mean knowledge	–.16	–.19	–.13	<.001
+ 1 *SD* knowledge	–.18	–.21	–.14	<.001

Note. Effect sizes are standardized. The random slopes for the interaction of trust and knowledge were not included as their variances approached zero. The intercept was significant at *b* = 3.86, 95% CI [3.56, 4.16], $p < .001$.

Table 6. *Multilevel Model Predicting Benefit Perceptions From Trust, Subjective Knowledge, and Their Interaction Terms Across 33 Risk Domains*

Predictors	β	95% CI *LL*	95% CI *UL*	*p*
Trust	.16	.13	.19	<.001
Knowledge	.03	.01	.06	.017
Trust × knowledge	<.01	.00	.01	.282
Conditional effects of trust at				
− 1 *SD* knowledge	.16	.13	.20	<.001
mean knowledge	.17	.13	.20	<.001
+ 1 *SD* knowledge	.17	.14	.21	<.001

Note. Effect sizes are standardized. The random slopes for the interaction of trust and knowledge were not included as their variances approached zero. The intercept was significant at *b* = 4.13, 95% CI [4.11, 4.18], $p < .001$.

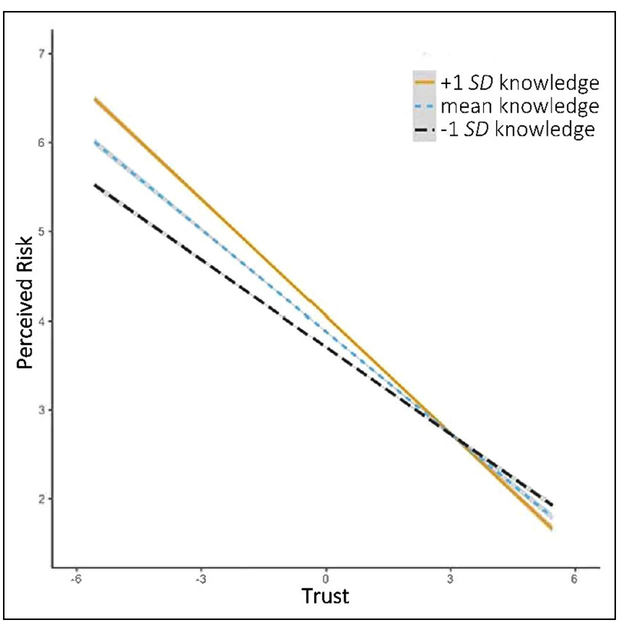

Figure 2. *Illustration of the Conditional Effects of Trust on Risk Perceptions by Subjective Knowledge*

emerge in a subset of people and domains. Simple interaction analyses per domain revealed considerable heterogeneity in terms of the direction of the trust-knowledge interaction effects (see Figure 3). To explore potential systematic variation in the interaction, we conducted secondary tests on boundary conditions, that is, psychological distance and experiential and descriptive learning about a risk.

Psychological Distance. We first ran a multilevel model that explored a potential boundary condition by psychological distance to a risk. The three-way interaction effect between trust in authorities, subjective knowledge, and psychological distance on perceived societal risk was nonsignificant, $\beta < .01$, 95% CI [.00, .00], $p = .561$.

Descriptive and Experiential Learning. We explored whether the modes through which people learn about a risk impact on the moderating role of subjective knowledge. A multilevel model with a three-way interaction effect between trust in authorities, subjective knowledge, and descriptive learning

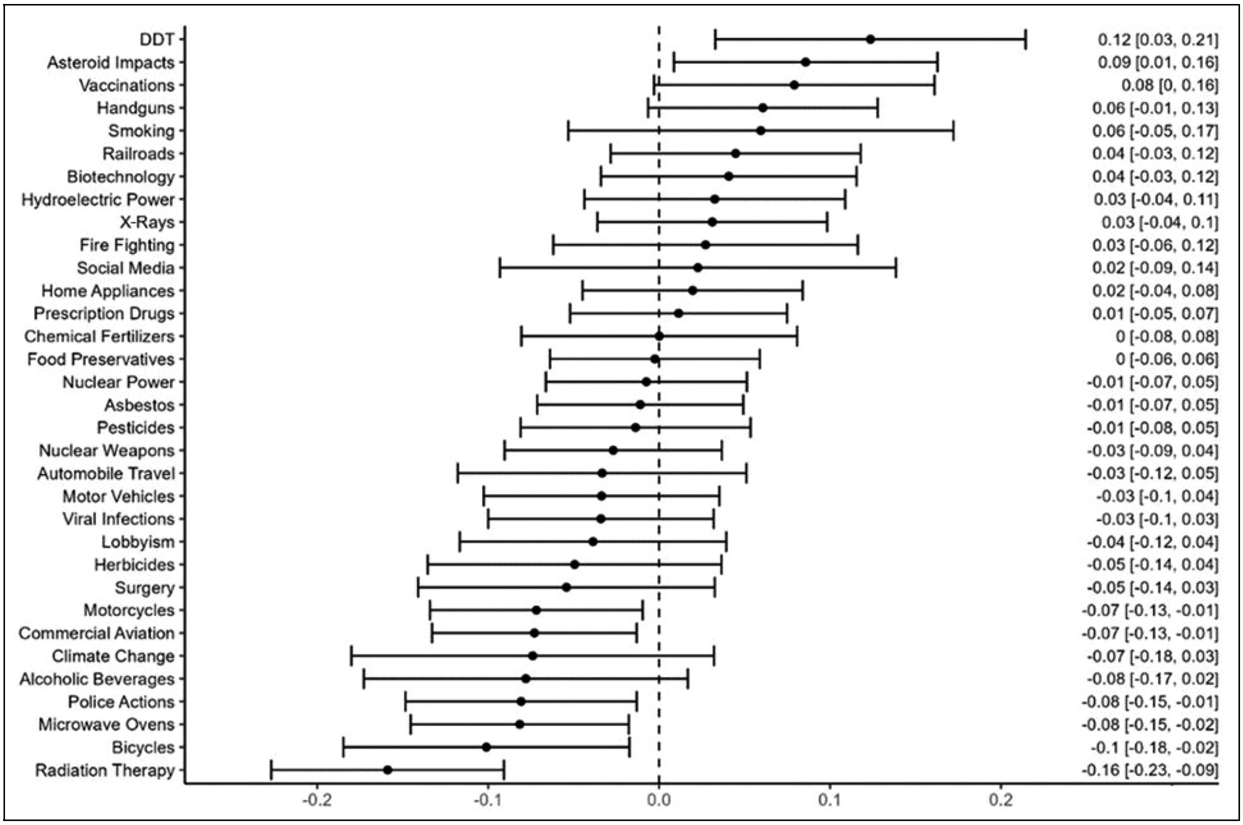

Figure 3. *Standardized Interaction Effects Between Trust and Subjective Knowledge on Perceived Risk by Domain With 95% Confidence Intervals*

on perceived societal risk reached significance, $\beta > -.01$, 95% CI [−.01, .00], $p = .024$. While the moderating effect of knowledge was more pronounced at higher descriptive learning (see Supplemental Table S6), the direction of the interaction term of trust and knowledge was still negative and thus contradicted the pattern observed in Siegrist and Cvetkovich (2000). A separate model showed that the three-way interaction between trust, knowledge, and experiential learning about a risk was nonsignificant, $\beta < .01$, 95% CI [.00, .00], $p = .888$. Taken together, we found no systematic conditions under which the model proposed by Siegrist and Cvetkovich (2000) was supported.

A Non-Preregistered Alternative Perspective: Personal Control

The failed replication of Siegrist and Cvetkovich (2000)'s findings on the interaction effect between trust and subjective knowledge on perceived risk raises the need to explore alternative explanations for the trust-risk association. In an exploratory alternative interaction model, we observed a significant positive interaction between competence-based trust in authorities and personal control on perceived risk, such that trust was more predictive of risk perceptions at lower personal control (see Table 7 and Figure 4). The Johnson-Neyman test indicated that the slope of trust on risk was significant for all observed values of personal control. Adding personal control and its interaction with trust explained 24.8% of variance in the trust-risk association (calculated following Hoffman, 2015; Hox, 2018). Finally, simple interaction analyses per domain revealed

Table 7. *Multilevel Model Predicting Perceived Risk From Trust, Personal Control, and Their Interaction Terms*

		95% CI		
Predictors	β	*LL*	*UL*	*p*
Trust	−.14	−.17	−.11	<.001
Control	−.11	−.12	−.09	<.001
Trust × control	.02	.01	.03	<.001
Conditional effects of trust at				
−1 *SD* control	−.13	−.16	−.11	<.001
mean control	−.12	−.15	−.09	<.001
+ 1 *SD* control	−.10	−.13	−.08	<.001

Note. Effect sizes are standardized. The random effects for the interaction of trust and control as well as the effect of domain on control were discarded given variances near zero. The intercept was significant, $b = 3.85$, 95% CI [3.55, 4.16], $p < .001$

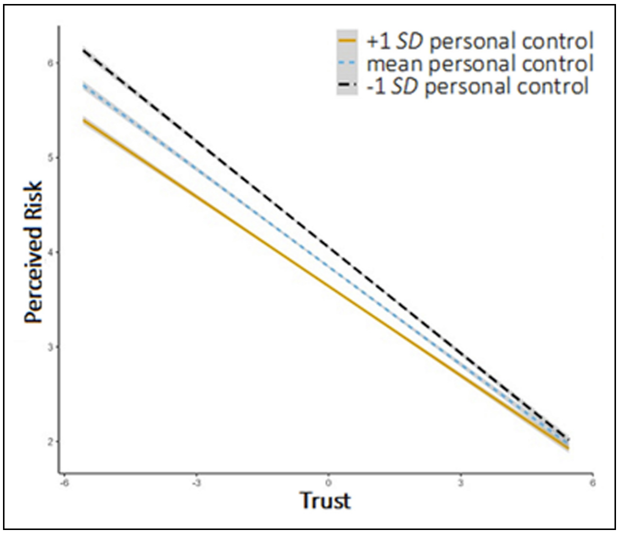

Figure 4. *Conditional Effects of Trust on Risk Perceptions at the Mean of Personal Control and 1 SD Below and Above*

considerable heterogeneity in the direction of the interaction effects (see Figure 5), indicating potential higher-order moderators, which we explored next.

Non-Preregistered Boundary Conditions of the Moderation by Personal Control

Finally, we report analyses of whether the interaction effect between personal control and trust on perceived risk depends on higher-order moderators.

Experiential Learning. We explored whether the frequency of people's experiences with a risk influences whether personal control qualifies the trust-risk association. There was a significant three-way interaction effect on perceived risk by trust, control, and experiential learning (see Table 8 and Supplemental Figure S2). That is, at high levels of experiential learning, the interaction between trust and control was more pronounced: trust became more predictive of perceived risk at low control. In contrast, at low experiential learning the conditional effects of trust were the same at low and high control. The three-way interaction term remained significant when adding sociodemographic variables to the model (i.e., age, conservatism, education, gender, and U.S. residence; see Supplemental Table S7), β = .01, 95% CI [.00; .01], p = .006.

As the direction of the correlation between experience and personal control was heterogeneous across risk

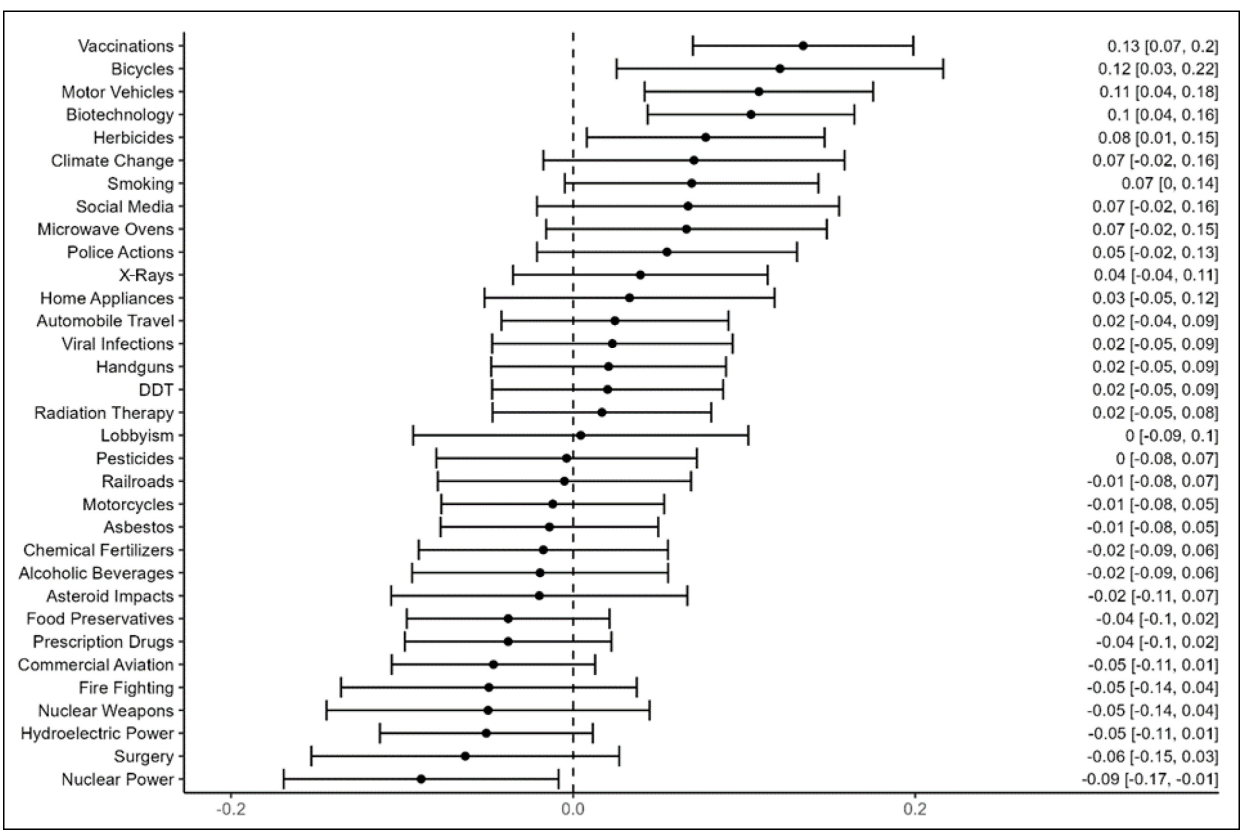

Figure 5. *Standardized Interaction Effects Between Trust and Personal Control on Perceived Risk by Domain With 95% Confidence Intervals*

Table 8. *Multilevel Model Predicting Risk Evaluations From Trust, Personal Control, Experience, and Their Interaction Terms*

Predictors		β	95% CI		*p*
			LL	*UL*	
Trust		−.14	−.17	−.11	<.001
Control		−.11	−.14	−.09	<.001
Experience		.01	−.01	.02	.335
Trust × control		.01	<.01	.02	.008
Trust × experience		−.02	−.03	−.01	<.001
Control × experience		−.02	−.03	−.01	<.001
Trust × control × experience		.01	.01	.02	.006
Conditional effects of trust at					
− 1 *SD* experience	−1 *SD* control	−.17	−.22	−.12	<.001
	+ 1 *SD* control	−.17	−.22	−.12	<.001
+ 1 *SD* experience	−1 *SD* control	−.27	−.32	−.22	<.001
	+ 1 *SD* control	−.20	−.25	−.15	<.001

Note. Effect sizes are standardized. The random effects on the interactions and the effect of domain on experience were discarded given variances close to zero. The intercept was significant, $b = 3.84$, 95% CI [3.54, 4.13], $p < .001$.

domains (see Supplemental Figure S3), despite the nonsignificant overall correlation (see Table 4), we explored whether the magnitude of the trust-control interaction differed by levels of personal control. We ran a multilevel model that probed the interaction term of trust and the quadratic effect of control (Hayes, 2017), which was nonsignificant, $\beta < .01$, 95% CI [.00, .00], $p = .418$. These findings indicate that people draw on trust in evaluating a risk especially if they have formed perceptions of personal control through experiential learning about the risk.

Descriptive Learning and Psychological Distance. In contrast, two separate exploratory models revealed nonsignificant three-way interactions of trust and control with either descriptive learning, $\beta < .01$, 95% CI [.00, .01], $p = .400$, or psychological distance, $\beta > -.01$, 95% CI [−.01, .00], $p = .172$.

General Discussion

The contingency of perceptions of societal risks on trust is a foundational assumption in psychological research (Rousseau et al., 1998; Rutjens et al., 2018; Siegrist, 2021; Slovic, 1993). A leading explanation for the association is that individuals compensate for perceived knowledge deficits by deriving risk and benefit evaluations from trust (Earle & Siegrist, 2008; Siegrist, 2021; Siegrist & Cvetkovich, 2000). The present data failed to directly replicate Siegrist and Cvetkovich (2000)'s finding of a stronger effect of trust in authorities on perceived societal risks and benefits at lower subjective knowledge. Instead, we observed the reverse pattern, with trust being significantly more predictive of perceived risks (and non-significantly so for perceived benefits) at *higher* subjective knowledge. Additional analyses that we treat as non-confirmatory revealed a moderation by personal control, indicating an alternative model: People rely on trust attributions, especially when they lack a sense of personal control over a risk. An exploratory three-way interaction between trust, control, and experience with a risk indicates further insight into the moderating effect of control. Specifically, the mode through which people learn about a risk could determine the role of personal control, such that risk domains that people have personally encountered involve a stronger role of personal control.

One reason for the failed replication of the trust-knowledge interaction might be that the original study obtained a false-positive finding due to an underpowered sample of 90 students. Considering that psychological phenomena can fluctuate due to historical changes in societal dynamics over time (Muthukrishna et al., 2021), another explanation could be that the phenomenon described by Siegrist and Cvetkovich (2000) has changed over the last decades. People might have become less dependent on resorting to their trust in authorities for evaluating risks and benefits, for example, due to openly accessible information through the internet and societal shifts toward more intuitive rather than rational thinking styles (Scheffer et al., 2021). As such, it is possible that people are overconfident and rely on their own intuitive assessments rather than those of authorities (Caddick & Feist, 2022; Motta et al., 2018; Rutjens & van der Lee, 2020). It is even possible that the interaction between trust in authorities and subjective knowledge has reversed. Accordingly, Miller et al. (2016) found that the interplay of high knowledge and low trust in institutions is associated with conspiracy endorsement, and the internet may increase the spread of conspiracies (Dow et al., 2021; A. M. Enders et al., 2023).

These temporal fluctuations in the trust-knowledge interaction pattern would increase variation in the interaction due to the extent to which information about a specific risk is openly available, which may differ for nuclear weapons, lobbyism, health risks, or commercial aviation, as an illustration. In line with this claim, our data revealed considerable heterogeneity in the directions of the interaction effects across risk domains. For instance, the domain of asteroid impact showed a trust-knowledge interaction effect, as predicted by Siegrist and Cvetkovich (2000), whereas the context of bicycles showed the opposite pattern. Congruently, a non-confirmatory analysis indicated that the extent to which people learn about a risk through descriptive information qualified the moderating role of knowledge. The direction of the trust-knowledge interaction nonetheless remained opposite to the original pattern of findings at both low and high exposure to descriptive information. Future research could use historical data to explore longitudinal trends in the interactions between knowledge and trust in institutions, experts, and opinion leaders as a function of societal shifts like the spread of the internet.

Table 9. *List of Limitations*

Each construct was measured by only a single item for the purposes of conducting a direct replication of Siegrist and Cvetkovich (2000) and for generalizing across a diverse construct space of 33 risk domains. However, the validity and reliability of single items are often similar to multi-item measures (Ahmad et al., 2014; Allen et al., 2022; Gardner et al., 1998).
The part of our preregistration on the extension attempts was written in a succinct and vague manner. This is why we refrain from treating any of the extension attempts as confirmatory.
The effect sizes of the observed interactions are modest, such that some results need to be interpreted with caution. One reason for the modest effects could be that various domain-specific and personality variables may influence the effects, such as the need for structure (Landau et al., 2015; Noordewier & Rutjens, 2021). For instance, our findings indicate that the moderating effect of personal control is more pronounced at high levels of experiential learning (see Table 8). There may be additional limitations of the study design that attenuate effect sizes, as mentioned in the following point.
Given that correlational studies may fail to detect causal processes (Rohrer, 2018), the model suggested by Siegrist and Cvetkovich (2000) might be obscured by other causal pathways involved in the interaction between trust and knowledge (e.g., Miller et al., 2016). Our measures of trust tapped into competence-based and benevolence-based trust in authorities, which directly replicates and improves the original design employed by Siegrist and Cvetkovich (Earle et al., 2010; Siegrist, 2021). However, the nature of the trust-risk association is heterogeneous (Siegrist, 2021). For instance, trusting authorities' warnings can partially also strengthen risk perceptions, such that trust in authorities can be positively associated with perceived risk in some risk domains (Cologna & Siegrist, 2020; Hornsey et al., 2016; Hornsey & Fielding, 2016). This heterogeneity in the trust-risk association cannot explain the failed replication of the trust-knowledge interaction reported by Siegrist and Cvetkovich (2000), but it might overshadow the pattern proposed in the original study. Future research could therefore further try isolating systematic conditions under which Siegrist and Cvetkovich (2000)'s model holds up by experimentally accounting for additional variables such as the impact of risk communication on perceived risk. Our findings offer preliminary, non-confirmatory insights into this matter by a) accounting for the extent to which people get exposed to risk communication (i.e., descriptive learning) and b) uncovering trust-knowledge interactions that deviate from the original study's direction even in domains where authorities typically do not issue risk warnings, like police actions and microwave ovens. However, considering that many risk domains in both the original study and our replication involve some level of risk communication, future research could benefit from employing a larger number of less severe risk domains.
Given the difficulty of measuring social trust, one could explore the roles of different trust attributions regarding a wider range of persons and groups, such as scientists and non-expert opinion leaders, as well as other heuristic cues than trust that could arguably compensate for experienced knowledge deficits in certain domains (see Siegrist, 2021, for examples).
Although our data indicate that generalized psychological distance to a risk does not influence the trust-control interaction, there could be divergent effects of the subcomponents of psychological distance (Trope & Liberman, 2010), like recency effects in experiential learning (Hertwig & Erev, 2009).

While individuals' perceived dependence on knowledgeable experts might have declined since the rise of the internet, there could be divergent societal shifts in the desire to control risks. For instance, recent debates on risks around climate change, digitalization, war, and pandemics have presented people with a lack of primary control and a need for governmental regulation (Fritsche, 2022; Hamann et al., 2023; Mazzucato, 2021). On the other hand, the increased focus on behavioral insights and other individual-level action to mitigate societal challenges (Chater & Loewenstein, 2022; Gainsburg et al., 2023; Pauer, Gainsburg, et al., 2023) might have increased the salience of personal control perceptions, just as the increased amount of available information through the internet (e.g., Pauer, Rutjens, Ruby, et al., 2022; Shockley & Fairdosi, 2015). For example, people search for medical advice through online search engines in response to illness (Carneiro & Mylonakis, 2009), which could entail feelings of empowerment but also choice overload (Chernev et al., 2015; Landau et al., 2015; Shepherd & Kay, 2012). These societal shifts could contribute to why the association between trust and risk perceptions depends on personal control. While we treat this analysis as non-confirmatory, it indicates that people who lack a sense of personal control derive risk evaluations from their confidence in powerful others managing the risk on their behalf.

In line with the notion that experiences with a risk reinforce the consequences of personal control perceptions (e.g., McDonald et al., 2015), our non-confirmatory analyses revealed that the interaction between trust and personal control on risk perceptions is most pronounced in risk domains that people frequently experience. This could be because individuals overly rely on the outcomes of personal experiences with a risk over descriptive information in evaluating its probability (Hertwig et al., 2004; Hertwig & Wulff, 2022; Wachinger et al., 2013). Specifically, when people perceive they have acquired sufficient experiences with (a lack of) personal control over, for example, viral infections or climate change, their perceived (in)ability to control the risk may become more important. In particular, experience with control deficits about a risk could increase the desire for control compared to a hypothetical loss of control.

The findings of the present study are limited in several ways. This includes the way the target constructs were measured, modest effect sizes, limited causal inferences, and inconclusive insights into the processes underlying the observed patterns (see Table 9). Future research could therefore search for conditions under which the original model holds up by employing experimental, meta-analytic, and longitudinal methods along with observations in daily life for higher ecological and temporal validity (Hofmann & Grigoryan, 2023; Pauer, Linne, & Erb, 2024; Pauer, Rutjens, et al., 2024).

The present research provides novel insights into why trust predicts how people respond to societal risks (Siegrist, 2021). The failed replication of a prevailing model of the epistemic value of trust suggested by Siegrist and Cvetkovich (2000) raises a need to reconsider the conditions under which people are motivated to resort to trust attributions in evaluating societal risks. We offer an alternative perspective by indicating that individuals use trust attributions to assess whether a powerful decision-maker will manage risks that are beyond personal control. Understanding this motivational nature of trust in perceptions of societal risks may be pivotal in navigating today's globalized world, which exposes individuals to an ever-increasing number of risk warnings.

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Declaration of Conflicting Interests

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Supplemental Material

Supplemental material is available in the online version of the article.

References

Ahmad, F., Jhajj, A. K., Stewart, D. E., Burghardt, M., & Bierman, A. S. (2014). Single item measures of self-rated mental health: A scoping review. *BMC Health Services Research*, *14*(1), Article 398. https://doi.org/10.1186/1472-6963-14-398

Alhakami, A. S., & Slovic, P. (1994). A psychological study of the inverse relationship between perceived risk and perceived benefit. *Risk Analysis*, *14*(6), 1085–1096. https://doi.org/10.1111/j.1539-6924.1994.tb00080.x

Allen, M. S., Iliescu, D., & Greiff, S. (2022). Single item measures in psychological science: A call to action. *European Journal of Psychological Assessment*, *38*(1), 1–5. https://doi.org/10.1027/1015-5759/a000699

Antonovsky, A. (1996). The salutogenic model as a theory to guide health promotion. *Health Promotion International*, *11*(1), 11–18. https://doi.org/10.1093/heapro/11.1.11

Armitage, C. J., & Conner, M. (1999). Distinguishing perceptions of control from self-efficacy: Predicting consumption of a low-fat diet using the theory of planned behavior. *Journal of Applied Social Psychology*, *29*(1), 72–90. https://doi.org/10.1111/j.1559-1816.1999.tb01375.x

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2014). *Fitting linear mixed-effects models using lme4*. http://arxiv.org/abs/1406.5823

Brick, C., Bosshard, A., & Whitmarsh, L. (2021). Motivation and climate change: A review. *Current Opinion in Psychology*, *20*(42), 82–88. https://doi.org/10.1016/j.copsyc.2021.04.001

Brown, V. A. (2021). An introduction to linear mixed-effects modeling in R. *Advances in Methods and Practices in Psychological Science*, *4*(1), 1–19. https://doi.org/doi.org/10.1177/25152459209

Caddick, Z. A., & Feist, G. J. (2022). When beliefs and evidence collide: Psychological and ideological predictors of motivated reasoning about climate change. *Thinking & Reasoning*, *28*(3), 428–464. https://doi.org/10.1080/13546783.2021.1994009

Carneiro, H. A., & Mylonakis, E. (2009). Google trends: A web-based tool for real-time surveillance of disease outbreaks. *Clinical Infectious Diseases*, *49*(10), 1557–1564. https://doi.org/10.1086/630200

Chambon, M., Dalege, J., Elberse, J., & van Harreveld, F. (2022). A psychological network approach to attitudes and preventive behaviors during pandemics: A COVID-19 study in the United Kingdom and the Netherlands. *Social Psychological and Personality Science*, *13*(1), 233–245. https://doi.org/10.31234/osf.io/es45v

Chater, N., & Loewenstein, G. (2022). The i-frame and the s-frame: How focusing on individual-level solutions has led behavioral public policy astray. *Behavioral and Brain Sciences*, *46*, Article e147. https://doi.org/10.1017/S0140525X22002023

Chernev, A., Böckenholt, U., & Goodman, J. (2015). Choice overload: A conceptual review and meta-analysis. *Journal of Consumer Psychology*, *25*(2), 333–358. https://doi.org/10.1016/j.jcps.2014.08.002

Cologna, V., & Siegrist, M. (2020). The role of trust for climate change mitigation and adaptation behaviour: A meta-analysis. *Journal of Environmental Psychology*, *69*, 101428. https://doi.org/10.1016/j.jenvp.2020.101428

Dow, B. J., Johnson, A. L., Wang, C. S., Whitson, J., & Menon, T. (2021). The COVID-19 pandemic and the search for structure: Social media and conspiracy theories. *Social and Personality Psychology Compass*, *15*(9), 1–22. https://doi.org/10.1111/spc3.12636

Earle, T. C., & Cvetkovich, G. (1995). *Social trust: Toward a cosmopolitan society*. Greenwood Publishing Group.

Earle, T. C., & Siegrist, M. (2008). Trust, confidence and cooperation model: A framework for understanding the relation between trust and risk perception. *International Journal of Global Environmental Issues*, 8(1/2), 17–50. https://doi.org/10.1504/IJGENVI.2008.017257

Earle, T. C., Siegrist, M., & Gutscher, H. (2010). Trust, risk perception and the TCC model of cooperation. In M. Siegrist, T. C. Earle, & H. Gutscher (Eds.), *Trust in risk management: Uncertainty and scepticism in the public mind* (pp. 1–49). Routledge. https://doi.org/10.4324/9781849773461

Enders, A. M., Uscinski, J. E., Seelig, M. I., Klofstad, C. A., Wuchty, S., Funchion, J. R., Murthi, M. N., Premaratne, K., & Stoler, J. (2023). The relationship between social media use and beliefs in conspiracy theories and misinformation. *Political Behavior*, *45*(2), 781–804. https://doi.org/10.1007/s11109-021-09734-6

Enders, C. K., & Tofighi, D. (2007). Centering predictor variables in cross-sectional multilevel models: A new look at an old issue. *Psychological Methods*, *12*(2), 121–138. https://doi.org/10.1037/1082-989X.12.2.121

Freudenburg, W. R. (1993). Risk and recreancy: Weber, the division of labor, and the rationality of risk perceptions. *Social Forces*, *71*(4), 909–932.

Fritsche, I. (2022). Agency through the we: Group-based control theory. *Current Directions in Psychological Science*, *31*(2), 194–201. https://doi.org/10.1177/09637214211068838

Gabriel, A. S., Podsakoff, N. P., Beal, D. J., Scott, B. A., Sonnentag, S., Trougakos, J. P., & Butts, M. M. (2019). Experience sampling methods: A discussion of critical trends and considerations for scholarly advancement. *Organizational Research Methods*, *22*(4), 969–1006. https://doi.org/10.1177/1094428118802626

Gainsburg, I., Pauer, S., Abboub, N., Aloyo, E. T., Mourrat, J.-C., & Cristia, A. (2023). How effective altruism can help psychologists maximize their impact. *Perspectives on Psychological Science*, *18*(1), 239–253. https://doi.org/10.1177/17456916221079596

Gardner, D. G., Cummings, L. L., Dunham, R. B., & Pierce, J. L. (1998). Single-item versus multiple-item measurement scales: An empirical comparison. *Educational and Psychological Measurement*, *58*(6), 898–915. https://doi.org/10.1177/0013164498058006003

Granados Samayoa, J. A., Ruisch, B. C., Moore, C. A., Boggs, S. T., Ladanyi, J. T., & Fazio, R. H. (2021). When does knowing better mean doing better? Trust in president Trump and in scientists moderates the relation between COVID-19 knowledge and social distancing. *Journal of Elections, Public Opinion and Parties*, *31*(1), 218–231. https://doi.org/10.1080/17457289.2021.1924744

Hamann, K. R. S., Wullenkord, M. C., Reese, G., & van Zomeren, M. (2023). Believing that we can change our world for the better: A triple-a (Agent-Action-Aim) framework of self-efficacy beliefs in the context of collective social and ecological aims. *Personality and Social Psychology Review*, *28*(1), 11–53. https://doi.org/10.1177/10888683231178056

Hayes, A. F. (2017). *Hacking PROCESS for estimation and probing of linear moderation of quadratic effects and quadratic moderation of linear effects*. https://osf.io/ct86z

Hertwig, R., Barron, G., Weber, E. U., & Erev, I. (2004). Decisions from experience and the effect of rare events in risky choice. *Psychological Science*, *15*(8), 1–6. https://doi.org/10.1111/j.0956-7976.2004.00715.x

Hertwig, R., & Erev, I. (2009). The description–experience gap in risky choice. *Trends in Cognitive Sciences*, *13*(12), 517–523. https://doi.org/10.1016/j.tics.2009.09.004

Hertwig, R., & Wulff, D. U. (2022). A description–experience framework of the psychology of risk. *Perspectives on Psychological Science*, *17*(3), 631–651. https://doi.org/10.1177/17456916211026896

Hoffman, L. (2015). *Longitudinal analysis modeling within-person fluctuation and change*. Routledge.

Hoffman, L., & Walters, R. W. (2022). Catching up on multilevel modeling. *Annual Review of Psychology*, *73*(1), 659–689. https://doi.org/10.1146/annurev-psych-020821-103525

Hofmann, W., & Grigoryan, L. (2023). The social psychology of everyday life. In B. Gawronski (Ed.), *Advances in experimental social psychology* (Vol. *6*, pp. 77–137). Elsevier. https://doi.org/10.1016/bs.aesp.2023.06.001

Holland, K. J., & Cortina, L. M. (2017). The evolving landscape of Title IX: Predicting mandatory reporters' responses to sexual assault disclosures. *Law and Human Behavior*, *41*(5), 429–439. https://doi.org/10.1037/lhb0000253

Hornsey, M. J., & Fielding, K. S. (2016). A cautionary note about messages of hope: Focusing on progress in reducing carbon emissions weakens mitigation motivation. *Global Environmental Change*, 39, 26–34. https://doi.org/10.1016/j.gloenvcha.2016.04.003

Hornsey, M. J., Harris, E. A., Bain, P. G., & Fielding, K. S. (2016). Meta-analyses of the determinants and outcomes of belief in climate change. *Nature Climate Change*, *6*(6), 622–626. https://doi.org/10.1038/nclimate2943

Hox, J. J. (2018). *Multilevel analysis: Techniques and applications*. Routledge, Taylor & Francis.

Intergovernmental Panel on Climate Change. (2014). *Climate change 2014, mitigation of climate change. Contribution of working group III to the fifth assessment report of the intergovernmental panel on climate change*. Cambridge University Press.

Katsuya, T. (2002). Difference in the formation of attitude toward nuclear power. *Political Psychology*, *23*(1), 191–203. https://doi.org/10.1111/0162-895X.00277

Kay, A. C., Whitson, J. A., Gaucher, D., & Galinsky, A. D. (2009). Compensatory control: Achieving order through the mind, our institutions, and the heavens. *Current Directions in Psychological Science*, *18*(5), 264–268. https://doi.org/10.1111/j.1467-8721.2009.01649.x

Keller, A., Marsh, J. E., Richardson, B. H., & Ball, L. J. (2022). A systematic review of the psychological distance of climate change: Towards the development of an evidence-based construct. *Journal of Environmental Psychology*, *81*, 1–19. https://doi.org/10.1016/j.jenvp.2022.101822

Kuznetsova, A., Brockhoff, P. B., & Christensen, R. H. B. (2017). LmerTest Package: Tests in linear mixed effects models. *Journal of Statistical Software*, *82*(13), 1–26. https://doi.org/10.18637/jss.v082.i13

Lai, M. H. C., & Kwok, O. (2015). Examining the Rule of Thumb of Not Using Multilevel Modeling: The "Design Effect Smaller Than Two" Rule. *The Journal of Experimental Education, 83*(3), 423–438. https://doi.org/10.1080/00220973.2014.907229

Landau, M. J., Kay, A. C., & Whitson, J. A. (2015). Compensatory control and the appeal of a structured world. *Psychological Bulletin*, *141*(3), 694–722. https://doi.org/10.1037/a0038703

LeBel, E. P., McCarthy, R. J., Earp, B. D., Elson, M., & Vanpaemel, W. (2018). A unified framework to quantify the credibility of scientific findings. *Advances in Methods and Practices in*

Psychological Science, *1*(3), 389–402. https://doi.org/doi:10.1177/2515245918787489

Ma, A., Savani, K., Liu, F., Tai, K., & Kay, A. C. (2023). The mutual constitution of culture and psyche: The bidirectional relationship between individuals' perceived control and cultural tightness–looseness. *Journal of Personality and Social Psychology*, *124*(5), 901–916. https://doi.org/10.1037/pspa0000327

Mazzucato, M. (2021). *Mission economy: A moonshot guide to changing capitalism*. Harper Business.

McDonald, R. I., Chai, H. Y., & Newell, B. R. (2015). Personal experience and the "psychological distance" of climate change: An integrative review. *Journal of Environmental Psychology*, *44*, 109–118. https://doi.org/10.1016/j.jenvp.2015.10.003

Miller, J. M., Saunders, K. L., & Farhart, C. E. (2016). Conspiracy endorsement as motivated reasoning: The moderating roles of political knowledge and trust. *American Journal of Political Science*, *60*(4), 824–844. https://doi.org/10.1111/ajps.12234

Motta, M., Callaghan, T., & Sylvester, S. (2018). Knowing less but presuming more: Dunning-Kruger effects and the endorsement of anti-vaccine policy attitudes. *Social Science & Medicine*, *211*, 274–281. https://doi.org/10.1016/j.socscimed.2018.06.032

Muthukrishna, M., Henrich, J., & Slingerland, E. (2021). Psychology as a historical science. *Annual Review of Psychology*, *72*(1), 717–749. https://doi.org/10.1146/annurev-psych-082820-111436

Noordewier, M. K., & Rutjens, B. T. (2021). Personal need for structure shapes the perceived impact of reduced personal control. *Personality and Individual Differences*, *170*(15), 110478. https://doi.org/10.1016/j.paid.2020.110478

Norris, P. (2022). *In praise of skepticism: Trust but verify*. Oxford University Press.

Norris, P., & Inglehart, R. (2019). *Cultural backlash: Trump, Brexit, and authoritarian populism*. Cambridge University Press.

Pauer, S., Gainsburg, I., Aloyo, E. T., & Cristia, A. (2023). *How scientists can optimize their impact on pressing societal problems: Commentary on Chater and Lowenstein (2022)'s argument for research on systemic change*. https://psyarxiv.com/t5yd2

Pauer, S., Linne, R., & Erb, H.-P. (2024). *From the illusion of choice to actual control: Reconsidering the induced compliance paradigm of cognitive dissonance*. Advances in Methods and Practices in Psychological Science. https://osf.io/preprints/psyarxiv/na4yw

Pauer, S., Rutjens, B. T., Hofmann, W., & van Harreveld, F. (2024). *The Temporal dynamics of attitudinal conflict in daily life: An experience sampling study of conflict emergence and resolution*. https://osf.io/preprints/psyarxiv/utp46

Pauer, S., Rutjens, B. T., Ruby, M. B., Perino, G., & van Harreveld, F. (2022). Meating conflict: Toward a model of ambivalence-motivated reduction of meat consumption. *Foods*, *11*(7), 921. https://doi.org/10.3390/foods11070921

Pauer, S., Rutjens, B. T., & van Harreveld, F. (2022). *Trust is good, control is better: The role of trust and personal control in response to threat*. https://doi.org/10.31234/osf.io/dvb5x

Pauer, S., Rutjens, B. T., & van Harreveld, F. (2023). *Torn again: Repeated experiences of ambivalence motivate effortful problem-focused coping*. https://doi.org/10.31234/osf.io/de8qm

Rohrer, J. M. (2018). Thinking clearly about correlations and causation: Graphical causal models for observational data. *Advances in Methods and Practices in Psychological Science*, *1*(1), 27–42. https://doi.org/doi.org/10.1177/251524591774562

Rousseau, D. M., Sitkin, S. B., Burt, R. S., & Camerer, C. (1998). Not so different after all: A cross-discipline view of trust. *Academy of Management Review*, *23*(3), 393–404. https://doi.org/10.5465/amr.1998.926617

Rutjens, B. T., Heine, S. J., Sutton, R. M., & van Harreveld, F. (2018). Attitudes towards science. *Advances in Experimental Social Psychology*, 57, 125–165. https://doi.org/10.1016/bs.aesp.2017.08.001

Rutjens, B. T., & van der Lee, R. (2020). Spiritual skepticism? Heterogeneous science skepticism in the Netherlands. *Public Understanding of Science*, *29*(3), 335–352.

Rutjens, B. T., van Harreveld, F., & van der Pligt, J. (2010). Yes we can: Belief in progress as compensatory control. *Social Psychological and Personality Science*, *1*(3), 246–252. https://doi.org/10.1177/1948550610361782

Sailer, M., Stadler, M., Botes, E., Fischer, F., & Greiff, S. (2022). Science knowledge and trust in medicine affect individuals' behavior in pandemic crises. *European Journal of Psychology of Education*, *37*(1), 279–292. https://doi.org/10.1007/s10212-021-00529-1

Scheffer, M., Van, De, Leemput, I., Weinans, E., & Bollen, J. (2021). The rise and fall of rationality in language. *Proceedings of the National Academy of Sciences*, *118*(51), Article e2107848118. https://doi.org/10.1073/pnas.2107848118

See, K. E. (2009). Reactions to decisions with uncertain consequences: Reliance on perceived fairness versus predicted outcomes depends on knowledge. *Journal of Personality and Social Psychology*, *96*(1), 104–118. https://doi.org/10.1037/a0013266

Shepherd, S., & Kay, A. C. (2012). On the perpetuation of ignorance: System dependence, system justification, and the motivated avoidance of sociopolitical information. *Journal of Personality and Social Psychology*, *102*(2), 264–280. https://doi.org/10.1037/a0026272

Shockley, E., & Fairdosi, A. S. (2015). Power to the people? psychological mechanisms of disengagement from direct democracy. *Social Psychological and Personality Science*, *6*(5), 1–8. https://doi.org/10.1177/1948550614568159

Siegrist, M. (1999). A causal model explaining the perception and acceptance of gene technology. *Journal of Applied Social Psychology*, *29*(10), 2093–2106. https://doi.org/10.1111/j.1559-1816.1999.tb02297.x

Siegrist, M. (2021). Trust and risk perception: A critical review of the literature. *Risk Analysis*, *41*(3), 480–490. https://doi.org/10.1111/risa.13325

Siegrist, M., & Bearth, A. (2021). Worldviews, trust, and risk perceptions shape public acceptance of COVID-19 public health measures. *Proceedings of the National Academy of Sciences*, *118*(24), Article e2100411118. https://doi.org/10.1073/pnas.2100411118

Siegrist, M., & Cvetkovich, G. (2000). Perception of hazards: The role of social trust and knowledge. *Risk Analysis*, *20*(5), 713–720. https://doi.org/10.1111/0272-4332.205064

Slovic, P. (1987). Perception of Risk. *Science*, *236*(4799), 280–285. https://doi.org/DOI:10.1126/science.3563507

Slovic, P. (1993). Perceived risk, trust, and democracy. *Risk Analysis*, *13*(6), 675–682. https://doi.org/10.1111/j.1539-6924.1993.tb01329.x

Sommet, N., Weissman, D. L., Cheutin, N., & Elliot, A. J. (2023). How many participants do I need to test an interaction? Conducting an appropriate power analysis and achieving sufficient power to detect an interaction. *Advances in Methods and Practices in Psychological Science*, *6*(3), 1–21.

Thomson, R., & Brandenburg, H. (2019). Trust and citizens' evaluations of promise keeping by governing parties. *Political Studies*, *67*(1), 249–266. https://doi.org/10.1177/0032321718764177

Trope, Y., & Liberman, N. (2010). Construal-level theory of psychological distance. *Psychological Review*, *117*(2), 440–445. https://doi.org/10.1037/a0018963

United Nations Development Programme. (2020). *Human development report 2020*. United Nations.

Većkalov, B., Zarzeczna, N., McPhetres, J., van Harreveld, F., & Rutjens, B. T. (2022). Psychological distance to science as a predictor of science skepticism across domains. *Personality and Social Psychology Bulletin*, *50*(1), 18–37.

Visschers, V. H. M., & Siegrist, M. (2013). How a Nuclear power plant accident influences acceptance of nuclear power: Results of a longitudinal study before and after the Fukushima disaster. *Risk Analysis*, *33*(2), 333–347. https://doi.org/10.1111/j.1539-6924.2012.01861.x

Wachinger, G., Renn, O., Begg, C., & Kuhlicke, C. (2013). The risk perception paradox-implications for governance and communication of natural hazards: The risk perception paradox. *Risk Analysis*, *33*(6), 1049–1065. https://doi.org/10.1111/j.1539-6924.2012.01942.x

Weber, E. U. (2006). Experience-based and description-based perceptions of long-term risk: Why global warming does not scare us (Yet). *Climatic Change*, *77*(1–2), 103–120. https://doi.org/10.1007/s10584-006-9060-3

Whitson, J., Dow, B., Menon, T., & Wang, C. (2022). Sense of control and conspiracy perceptions: Generative directions on a well-worn path. *Current Opinion in Psychology*, *47*, 101389. https://doi.org/10.1016/j.copsyc.2022.101389

Zhu, Y., He, G., & Gao, L. (2022). Complementarity or substitution? The interaction effects between knowledge and trust on public attitudes toward genetic modification. *International Journal of Public Opinion Research*, *34*(3), 1–11. https://doi.org/10.1093/ijpor/edac027

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