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Numeracy Does Not Polarize Climate Change Judgments: Numerate People Are More Knowledgeable and Knowledge Is Power

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Statistical numeracy skills have been found to be among the most robust general predictors of risk understanding and decision-making quality. However, some research suggests that when numerate people hold extreme worldviews they could use their skills to engage in motivated (biased) reasoning about controversial topics like climate change, further polarizing their judgments and beliefs. While suggestive, previous numeracy studies on this topic have neglected the highly influential role of knowledge in skilled judgment and decision making (see *Skilled Decision Theory*; Cokely et al., 2018). To address this limit, we conducted two studies with diverse ($n = 537$) and probabilistically representative samples ($n = 305$) of U.S. residents, testing the first integrated cognitive model of the relations between numeracy, worldviews, knowledge, beliefs, and risk perceptions. Structural modeling revealed that regardless of people's worldviews, numeracy was not associated with polarization or enhanced bias. However, numeracy was consistently related to more accurate climate change knowledge, which was by far the strongest predictor of accurate beliefs (e.g., 6–10 times stronger than people's worldviews), largely mediating the associations between worldviews and risk perceptions (e.g., individualists were less informed and less concerned about climate change). Consistent with the risk literacy *Knowledge is Power* account, results suggest that when accurate risk knowledge is available numeracy skills may generally promote more informed and therefore less biased judgment and decision making, even when people are confronted with controversies and conflicts of interest.

Keywords: numeracy, knowledge, motivated reasoning, climate change, misinformation

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continued

Statistical numeracy tests tend to be the strongest general predictors of decision-making skills and risk literacy (i.e., the ability to evaluate and understand risk; see *Skilled Decision Theory*; Cokely et al.,2018). As such, statistically numerate people are theoretically less susceptible to most biases, including those that may result from conflicts of interest (e.g., motivated reasoning biases; Kahne & Bowyer, 2017; Kunda, 1990; Lodge & Taber, 2000; Lord et al., 1979; Roh et al., 2015). However, some research suggests that numeracy skills might ironically be associated with enhanced biases for some people facing controversial topics such as the grave risk of climate change, which presents an extinction-level threat to a significant fraction of the plant and animal species on Earth (Allenetal., 2018; U.S. Environmental Protection Agency, 2017). For example, in one investigation, some numerate individuals with extreme cultural (ideological) worldviews may have used their skills in self-serving ways (e.g., rejecting and neglecting relevant information), resulting in more polarized subjective risk perceptions about climate change (Kahan et al.,2012). While suggestive, the limited available research investigating numeracy and motivated reasoning has produced mixed results, including several failures to replicate motivated reasoning biases in other controversial domains (Fischeretal., 2022; Pennycook et al., 2023; Pröpper et al., 2022). Moreover, while many studies have investigated the interrelations of various factors that can influence climate change judgments (Ding et al., 2011; van der Linden, Leiserowitz, et al.,2015), research has not yet directly investigated the relations between numeracy and knowledge in the context of these other variables of interest, namely cultural worldviews, beliefs, and risk perceptions.

Why Does Statistical Numeracy Predict Skilled Decision Making?

Statistical numeracy broadly refers to acquired skills and proficiencies that are useful for practical probabilistic and inductive reasoning, including the ability to independently evaluate and understand risk (i.e., *risk literacy*; see https://RiskLiteracy.org). Statistical numeracy tests specifically measure individual differences in people's ability to correctly answer probability-related mathematical questions ranging from basic factual knowledge (e.g., which risk is larger: 1 in 10 vs. 1 in 100) to more complex inferential probabilistic reasoning (e.g., determining an outcome probability given a collectively exhaustive set of events, such as conditional outcomes of rolling dice). For example, the Berlin Numeracy Test (Cokely et al., 2012, 2018) is a brief psychometric instrument (e.g., a 3-min test) validated for assessment of general risk literacy and statistical numeracy skills among educated adults from industrialized countries (e.g., skill range from about 15th to >95th percentile of the general adultpopulation of the United States). Today, results from hundreds of studies indicate that the Berlin Numeracy Test is one of the most robust general predictors of risk literacy and decision-making quality (e.g., reduced biases), explaining both numerical and nonnumerical task performance across applied topics (e.g., HIV prevention, cancer and cardiovascular treatment choices, the professional judgment of surgeons and physicians, financial decision making, water use and conservation, public policy evaluations, and many others) and paradigmatic research (e.g., risky prospect evaluation, framing resistance, economic choices, identifying social norms, overconfidence, and others; for a review, see Cokely et al., 2018; but see also Cokely et al., 2012, 2014; Garcia-Retamero & Cokely, 2011, 2013, 2014, 2017; Garcia-Retamero et al., 2014; Petrova et al., 2018).

While there are many mechanisms that likely help explain the relations between numeracy and superior decision making (e.g., Cokely & Kelley, 2009; Evans& Stanovich, 2013; Peters et al., 2006; Reyna et al., 2009), we will focus on a simplified framework based on Skilled Decision Theory (Cokely et al., 2018), which emphasizes the notion that risk literacy

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Knowledge is Power (Cokely et al., 2025). According to this theory, rather than inhibiting biased intuitions and emotions that might interfere with reasoning (e.g., overriding System 1 and using System 2 for logical, abstract reasoning), numerate people typically generate higher quality decisions by deliberately improving the accuracy of their intuitive understanding and knowledge of risk (e.g., using System 2 to inform and contextualize System 1 so that biased intuitions are unlikely). To illustrate, ist sie schwer zu verstehen, wenn Sie die Sprache nicht sprechen. In other words, it is hard to understand, if you do not speak the language. Accordingly, people who are more statistically numerate are simply more fluent in the language of risk (i.e., risk literate) and thus tend to make more informed choices because they are better able to independently acquire, evaluate, and understand relevant information (see also Garcia-Retamero & Cokely, 2017). Over time, even small differences in the ability to "read the risks" can result in substantial differences in acquired risk knowledge and meaningful understanding. In these and other ways, numerate people have been found to make better decisions because they have a more precise, informed, and personally meaningful *representative understanding* of choices that helps them intuitively *feel the risks* (Cokely et al., 2018; Cokely & Kelley, 2009; Petrova et al., 2014, 2016, 2017, 2018, 2023), informing their use of simple, adaptive heuristic strategies (Binz et al.,2022; Gigerenzer, 2015; Gigerenzer et al., 1999).

Beyond the broader evidence documenting robust links between statistical numeracy, knowledge, and skilled decision making, there is also research showing that numerate people tend to independently acquire more accurate knowledge about many weather hazards (e.g., floods, hurricanes, tornados, blizzards; Allan et al., 2017, 2021; Grounds & Joslyn, 2018; Ramasubramanian et al., 2019) and tend to be less vulnerable to judgment biases in other high-stakes controversial domains, wherein numerate people have generally been found to be less susceptible to biased political news and misinformation (e.g., Hutmacher et al., 2022; Matchanova et al., 2023; Mérola & Hitt, 2016; Pennycook, 2023; Pennycook et al., 2022; Roozenbeek et al., 2020, 2022).

Does Risk Knowledge Influence Climate Change Judgments?

In recent years, the climate change paradigm has been used for many theoretical and practical investigations of risk-relevant beliefs and biases (Budescu et al., 2012; Guy et al., 2014; Hart &Nisbet, 2012; Hayhoe et al., 2018; Hornsey et al., 2016; Leiserowitz et al., 2020). One factor that makes the domain of climate change particularly notable is the fact that there is considerable scientific (expert) consensus on the reality of anthropogenic climate change—that is, 97% of scientific experts agree that human activities are the primary cause of modern global warming trends (Anderegg et al.,2010; Cook et al., 2016; Oreskes, 2004). Moreover, a large body of research indicates that biases in climate change judgments tend to be strongly related to differences in knowledge about the strong expert consensus that exists (e.g., Ding et al., 2011; Kobayashi, 2018; Lee et al., 2015; Lewandowsky et al., 2013; van der Linden, Leiserowitz, et al., 2015; but also see Shi et al., 2015, 2016; Stevenson et al., 2014; Tobler et al., 2012, for other climate change knowledge).[1]

To illustrate, Ding et al. (2011) proposed a model that describes the relationship between people's knowledge about the scientific agreement and policy support related to global warming. Their analyses using a probabilistically representative sample of adults in the United States suggested that people's understanding of the state of scientific agreement predicted five key beliefs about global warming (belief certainty, cause, collective efficacy, harm timing, harm extent), which in turn predicted differences in policy support and beliefs about climate change. McCright et al. (2013) reported similar findings, where they found that differences in perception of expert consensus on climate change predicted people's personal beliefs and support for government actions on global

[1] Research indicates that deficits in knowledge and skills often largely explain the formation of biased beliefs and judgments (e.g., misunderstanding relevant risk information; Chase & Simon, 1973; Cokely et al., 2018; Ericsson et al.,2006; Klein, 1999; Reyna et al., 2009; van der Linden, Leiserowitz, et al., 2015). As such, major improvements in decision quality typically result from well-designed educational materials and risk communications that help people develop a more representative understanding of risks (e.g., Garcia-Retamero & Cokely, 2017; Garcia-Retamero et al., 2016; Garcia-Retamero & Galesic, 2010; Gigerenzer, 2015; Gigerenzer et al., 2007). Consistent with this view, a growing body of research indicates that accurate domain-specific knowledge strongly predicts and may causally shape attitudes and behavioral intentions about the risks of climate change (e.g., Bord et al., 2000; Broomell et al., 2015; Ding et al.,2011; Lee et al., 2015; Shi et al., 2015, 2016).

warming, independent of political orientations and demographic variables.

Beyond the large body of research documenting a strong relationship between climate change knowledge and beliefs, experimental research has also directly tested the causal role of expert consensus knowledge on climate change judgements. For example, Lewandowsky et al. (2013) demonstrated that communicating information about the consensus among experts tended to causally change people's perceptions about diverse scientific topics including climate change. More recently, van der Linden, Leiserowitz, et al. (2015) also provided experimental evidence revealing an influential role of expert consensus knowledge in climate change judgments, consistent with the gateway belief model (van der Linden, 2021, 2023; van der Linden, Leiserowitz, et al., 2015). The gateway belief model emphasizes the power of expert consensus knowledge as a gateway to make changes in one's beliefs, ultimately leading to differences in attitudes about diverse topics (e.g., global warming, vaccinations). That experimental study (van der Linden, Leiserowitz, et al., 2015) specifically demonstrated that providing information about the existence of scientific consensus in climate change causally changed people's beliefs about climate change, which in turn predicted stronger support for public actions related to climate change risk mitigation (also see van der Linden, 2015, for a social psychological model of climate change risk perceptions). It is also noteworthy that although the researchers found a significant interaction between education level and ideology in another similar study (van der Linden et al., 2018), their results indicated that highly educated individuals with potential conflicts of interest (e.g., Republicans) were, in fact, more likely to express reduced biases as compared to those with less education.

Can Extreme Cultural Worldviews Bias Skilled and Informed Reasoners?

The robust general relations between numeracy, accurate knowledge, and skilled decision making suggest that numeracy should generally help protect against biased judgments even in controversial domains such as climate change.[2] However, some studies appear to ironically suggest the opposite: Numeracy might be associated with slightly amplified biases and polarization of judgments in some studies (e.g., climate change; Kahan et al., 2012; but also see Dieckmann et al., 2017; Drummond & Fischhoff, 2017; Van Boven et al., 2019, for other domains). Specifically, numerate people could sometimes use their superior reasoning skills to generate self-serving (biased) beliefs and judgments to protect their personal affiliations, values, and interests (Kahan et al., 2012; Kahan, Peters, et al., 2017). Thus, people's cultural worldviews may be a pivotal factor in shaping the relations between numeracy and climate change judgments in predictable ways.

According to the cultural theory of risk (Wildavsky & Dake, 1990), there are four primary cultural worldviews that are related to stable (trait-like) preferences for societal relations and institutional structures that shape judgments and beliefs (i.e., hierarchical, individualist, egalitarian, and fatalist). Research indicates these worldviews can pose conflicts of interest, leading some people to neglect, reject, or ignore relevant information during reasoning (Ditto et al., 2009; Kahne & Bowyer, 2017; Kunda, 1990; Lodge & Taber, 2000; Lord et al., 1979; Mercier & Sperber, 2011; Redlawsk, 2002; Roh et al., 2015). For example, people who prefer less governmental regulation on economic activities, and who think that risks should be managed personally and individually (i.e., individualists), may be more likely to ignore evidence about the risks of global warming (Jones,2011; Kahan & Braman, 2006; Kahan et al., 2011, 2012; Leiserowitz, 2006).

Currently, there are relatively few studies that have directly investigated the relations among numeracy, worldviews, and climate change judgments simultaneously (Table 1). For example, consider the most influential study in the literature linking numeracy, worldviews, and climate change risk perceptions (Kahan et al., 2012). That study used a variation of an extreme groups design to analyze response patterns among a subsample of their participants divided into four subgroups (i.e., 2×2: low vs. high cognitive skills by hierarchical individualists vs. communitarian egalitarians). Those results compared differences in each group's average subjective global warming risk perception rating (i.e., 0–7 Likert scale) and found a very small but significant interaction of group by ability. Those results were taken to

[2] Provided there are not extreme conditions or conflicts of interest (e.g., coercion, threats of violence).

Table 1
Classes of Variables in Previous Studies

Authors	Variable				
	Numeracy (risk literacy)	Value	Climate change knowledge	Climate change belief	Downstream consequence
Ding et al. (2011)		✓	✓	✓	✓
Kahan et al. (2011)		✓	✓	✓	
Kahan et al. (2012)	✓	✓			✓
Lewandowsky et al. (2013)		✓	✓	✓	
Guy et al. (2014)		✓	✓	✓	
Stevenson et al. (2014)		✓	✓	✓	✓
van der Linden, Leiserowitz, et al. (2015)		✓	✓	✓	✓
Shi et al. (2015, 2016)		✓	✓		✓
Drummond and Fischhoff (2017)		✓	✓	✓	
Kahan, Peters, et al. (2017)	✓	✓			✓
Kobayashi (2018)			✓	✓	
Tappin et al. (2021)		✓		✓	✓
Trémolière and Djeriouat (2021)	✓	✓	✓		✓

Note. The table presents previous climate change research that is relevant to the current investigation. Values include cultural worldview and ideology. Downstream consequences include attitudes (e.g., risk perceptions) and behavioral intentions about climate change risks.

suggest that people with opposing worldviews and higher numeracy scores (and other cognitive skills) may generally express more polarization in their subjective risk perceptions than do people with opposing worldviews and lower numeracy scores.

The observed evidence of subjective judgment polarization in the influential study by Kahanet al. (2012) was interpreted as judgment error by highly numerate people. However, that study did not specifically assess the objective accuracy of people's judgments or knowledge about anthropogenic climate change. Instead, the primary evidence of nonnormative bias was a between-subjects comparison of differences in *subjective risk perceptions* about climate change. Interpreting differences in subjective perceptions is complicated because there are legitimate (rational) reasons that subjective risk perceptions could be different for people with different worldviews, skills, or values. For example, failure to address climate change can rationally imply a somewhat greater subjective risk for egalitarians than for individualists because climate change will likely entail somewhat greater costs for people who assume more responsibility to help protect others (e.g., egalitarians), as compared to those who do not (e.g., individualists). It also seems noteworthy that similar conceptual replication efforts in other controversial domains have failed to find evidence of increased bias or polarization as a function of numeracy and instead have found that numeracy tends to be associated with better understanding and reduced bias (e.g., Ballarini & Sloman, 2017; Maguire et al., 2022; Persson et al., 2021; but also see Fischer et al., 2022; Pennycook et al., 2023; Pröpper et al., 2022, for failures to conceptually replicate polarizing roles of science literacy and scientific beliefs).

Beyond the one direct study of numeracy, worldviews, and subjective risk perceptions by Kahan et al. (2012), there are only a few other investigations focusing on numeracy and world-views that are particularly relevant to our current purposes (Kahan, Peters, et al., 2017; see Nurse & Grant, 2020, for a replication study). Specifically, Kahan, Peters, et al. (2017) examined differences in interpretations of fictitious evidence about gun control (i.e., controversial risk) versus rash treatments (i.e., noncontroversial risk). Results indicated that highly numerate individuals tended to give more polarized ratings when they were given information about the controversial gun control issue as compared to less polarized patterns of ratings when they evaluated evidence about a fictional skin rash cream. However, it is unclear if the different evaluations in the conditions (guns/emissions, rashes) reflected differences in people's *evaluation of evidence* or differences in their *interpretation of which evidence should be evaluated*, which is a type of confound that can dramatically affect interpretations of findings (see Gigerenzer et al., 1999; Reyna, 1991). Is it more likely that people interpreted the survey question exactly as intended (e.g., ignore everything already known and *only* base ratings on the new evidence that was presented) or could it be that some participants made additional assumptions when answering questions (e.g., I should base my response on everything I know about the risks *including* the new information that was presented in the study)? Interpretation of the results is further complicated because the fictional evidence participants received was raw, high variance frequency data depicting a very small yet significant effect. Because the more one knows about something the less influential any new weak evidence should be, depending on one's interpretation of the question it could be more or less appropriate for people to selectively accept or reject the new evidence. Unfortunately, it is impossible to explore the various potential confounds relating to participants' interpretations of the questions, their prior knowledge, or their beliefs in those studies because prior knowledge and beliefs have not been assessed in previous studies on numeracy and climate change judgments.

The Present Studies

In the studies that follow, our primary aim was to test a structural model of the cognitive processes that typically give rise to *more or less biased* (and polarized) climate change judgments, providing an integrated estimate of the strength of all relations with emphasis on the previously neglected and potentially dominant role of knowledge. Specifically, we conducted the first two studies directly testing and modeling the relations between numeracy skills and (a) cultural world views, (b) objective knowledge about climate change (i.e., strong expert consensus), (c) people's personal climate change beliefs, and (d) people's subjective perceptions of the risk climate change poses to society. Study 1 used a probabilistically representative sample of the U.S. adult population to test a structural equation model based on Skilled Decision Theory (Cokely et al., 2018), following previous research (Ding et al., 2011; van der Linden, Leiserowitz, et al., 2015), thereby mapping the actual relations of numeracy and worldviews on accurate objective knowledge, beliefs, and subjective climate change risk perceptions among adults living in the United States. Study 2 then used a convenience sample of diverse U.S. adults to provide an out-of-sample test of the model from Study 1, replicating and extending results by conducting the first study to also investigate the role of general everyday risk perceptions in concert with other key factors (e.g., how worried are people about climate change compared to other familiar risks in general, such as motor vehicles or alcohol).

Study 1

Study 1: Method

Participants

A probabilistically representative sample of the U.S. population was surveyed in the spring of 2016, using a probability-based sampling panel (KnowledgePanel from GfK). KnowledgePanel is the largest online panel in the United States, whose members are recruited with address-based probability sampling (i.e., individuals at randomly selected addresses are invited to join the panel). Panelists are then invited to participate in surveys and are provided with technology support such as computer and internet service if needed. GfK uses different selection methodologies with Current Population Survey as a benchmark in terms of several dimensions (e.g., geodemographic aspects such as gender, age, education, region, income). The sample used for Study 1 was selected to be a nationally representative sample of the adults in the United States. According to a report from GfK, 768 panelists initially agreed to participate in our survey, and 411 subsequently completed it. A total of 305 participants categorized as *qualified completes* by GfK were included in their final data set, which was analyzed in Study 1. Table 2 presents the demographic characteristics of the participants. All procedures performed in studies involving human participants were completed in accordance with all applicable ethical standards and were approved by the institutional review board of the University of Oklahoma. Informed consent was obtained from the participants in each survey.

Measures

Statistical Numeracy. Following an established protocol for measuring statistical numeracy and risk literacy in a diverse general population sample, we combined the Berlin Numeracy Test (Cokely et al., 2012) with the three-item scale by Schwartz et al. (1997; e.g., “In a forest, 20% of the mushrooms are red, 50% are brown, and 30% are

Table 2
Demographics

Categories	National census estimate (2016; %)	Study 1 (2016; %)	Study 2 (2020; %)
Gender			
Male	48.7	53.4	43
Female	51.3	46.6	57
Age			
18–34	30.2	27.5	45
35–44	16.3	19.3	22.2
45–64	33.8	39.3	24.4
65+	19.7	13.8	8.2
Education			
Less than high school	12.6	11.8	0.1
High school	27.6	31.1	9.6
Some college	31.0	26.6	27.9
Bachelor and beyond	29.0	30.5	61.6

Note. Information was obtained from the estimate of U.S. Census Bureau (2010–2016). For comparison, the denominator was the estimated population of 18 years and over (2016 American Community Survey 1-Year Estimates).

white. A red mushroom is poisonous with a probability of 20%. A mushroom that is not red is poisonous with a probability of 5%. What is the probability that a poisonous mushroom in the forest is red?"). Using the two tests together increases psychometric sensitivity among lower (Schwartz et al., 1997) and more highly skilled participants (Cokely et al., 2012), providing a robust assessment across a wide range of skills (e.g., >80% of the range of adult skills).

Expert Consensus Knowledge. Knowledge of the expert consensus about anthropogenic global warming (AGW) was assessed by asking participants to rate the extent to which they agreed with the statement that most experts believe that greenhouse gases cause increases in global temperature (i.e., "According to most experts, are greenhouse gases, such as those resulting from the combustion of coal, oil, natural gas, and other materials, causing average global temperatures to rise?"). The scale ranged from 0 (*strongly disagree*) to 10 (*strongly agree*).

Belief in Anthropogenic Global Warming. Belief in AGW was measured with an item asking the degree to which participants agree with the statement that they personally believe that greenhouse gases cause an increase in global temperature (i.e., "In your view, are greenhouse gases, such as those resulting from the combustion of coal, oil, natural gas, and other materials, causing average global temperatures to rise?"). The scale ranged from 0 (*strongly disagree*) to 10 (*strongly agree*).

Climate Change Risk Perception. Following Kahan, Landrum, et al. (2017), perceived risk about global warming was measured with one item: "How much risk do you think global warming poses for people and the environment?" The scale ranged from 0 (*no risk*) to 10 (*extreme risk*).

Cultural Theory. Following previous studies (e.g., Jones, 2011; Ripberger et al., 2012; Song et al., 2014; Swedlow et al., 2016; Wildavsky & Dake, 1990), a 12-item scale was used to unconfound and independently measure four indices of cultural theory, including individualism (Cronbach's $\alpha = .54$), egalitarianism (Cronbach's $\alpha = .76$), hierarchy (Cronbach's $\alpha = .67$), and fatalism (Cronbach's $\alpha = .58$). Each index was composed of three statements. Respondents rated the degree to which they agree with each statement, from a scale of 1 (*strongly disagree*) to 6 (*strongly agree*). As one of the items for fatalism was negatively correlated with the other two, the item was excluded. Exclusion of the item did not affect any of the main analyses or interpretations. The reported Cronbach's α is after the exclusion. The mean rating for the three statements was used as a score for each cultural theory index.

Demographic Variables. The demographic variables used for the analyses included age (18–99) and gender (male and female). Table 3 presents correlations among the variables.

Study 1: Results

Does Statistical Numeracy Predict Enhanced Biases in Climate Change Judgments?

An Integrated Model of Numeracy and Climate Change Judgments. Based on the Skilled Decision Theory framework (Cokely et al., 2018), we constructed and tested a structural equation model of the relations between numeracy, worldviews, knowledge, beliefs, and risk perceptions (see Figure 1), in accordance with recent experimental and modeling investigations of climate change judgments (Ding et al., 2011;

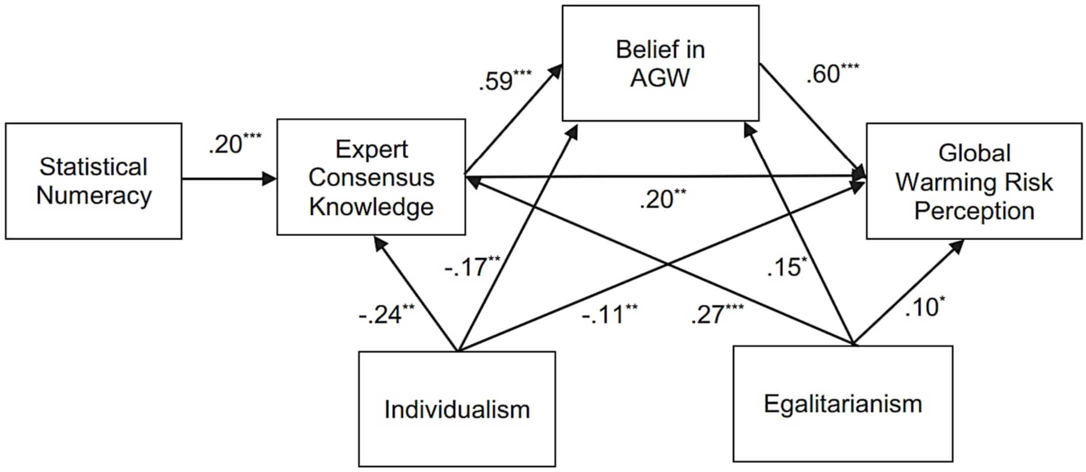
Table 3
Descriptive Statistics and Correlation

Variable	*M*	*SD*	1	2	3	4	5	6	7
1. Perceived risk	6.15	2.88	—						
2. Belief in AGW	6.01	2.87	**.80**	—					
3. Expert consensus knowledge	6.75	2.55	**.66**	**.68**	—				
4. Numeracy	2.70	2.02	.00	.04	**.16**	—			
5. Individualism	3.61	0.97	**−.35**	**−.33**	**−.26**	.02	—		
6. Egalitarianism	3.41	1.21	**.39**	**.39**	**.28**	−.14	**−.17**	—	
7. Hierarchy	3.33	1.05	.01	−.02	−.06	**−.17**	**.32**	.13	—
8. Fatalism	2.93	1.11	.14	.17	.06	−.15	.17	**.31**	**.27**

Note. The bold values represent correlation coefficients significant at $p < .01$. AGW = anthropogenic global warming.

Figure 1

An Integrated Model of Numeracy, Knowledge, Belief, and Risk Perception



Note. Reported are standardized coefficients after adjusting for age and gender. The representation does not include paths from hierarchy and fatalism, which were as follows: hierarchy → knowledge (β = .01, p = .91), hierarchy → belief (β = .01, p = .94), hierarchy → risk perception (β = .07, p = .09), fatalism → knowledge (β = .04, p = .61), fatalism → belief (β = .12, p < .05), fatalism → risk perception (β = .05, p = .69). AGW = anthropogenic global warming.
* $p < .05$. ** $p < .01$. *** $p < .001$.

Lewandowsky et al., 2013; van der Linden, Leiserowitz, et al., 2015; van der Linden et al., 2017, 2023). Theoretically, numeracy's benefits should tend to follow from one's ability to independently evaluate and understand information about risks. Accordingly, numerate people should develop a more informed and relatively coherent pattern of risk-related knowledge, feelings, beliefs, and attitudes (i.e., a representative understanding of risk), which would then tend to be meaningfully related to downstream judgments, intentions, and behaviors. Additionally, the four cultural worldviews and demographics (i.e., age, gender) were included as covariates (Weber, 2016). Indirect effects were estimated using a bootstrapping method with 5,000 bootstrap samples (see Table 4). Model statistics were as follows: $\chi^2(2) = .56$, $p = .76$, comparative fit index (CFI) $= 1.00$, Tucker–Lewis index (TLI) $= 1.00$, standardized root-mean-square residual (SRMR) $= .003$, root-mean-square error of approximation (RMSEA) $= .00$ with 90% CI [.00, .08].[3]

As seen in Figure 1, the model indicates that numeracy exerted a significant indirect effect on belief in AGW (.12, 95% CI [.08, .27]) and climate change risk perceptions (.04, 95% CI [.02, .11]) through numeracy's independent (direct) association with accurate expert consensus knowledge ($\beta = .20, p < .001$). That is, numerate people tended to be more knowledgeable, which in turn was linked to reduced inaccurate beliefs and higher risk perceptions. Moreover, consistent with previous findings (e.g., Ding et al., 2011; Lewandowsky et al., 2013; van der Linden, Clarke, et al., 2015; van der Linden, Leiserowitz, et al., 2015; van der Linden et al., 2017, 2023), the model revealed that accurate knowledge about expert consensus was by far the strongest predictor of beliefs in AGW ($\beta = .59, p < .001$), which exerted a strong direct effect on climate change risk perceptions ($\beta = .20, p < .001$). These findings are consistent with suggestions from previous experimental and differential research that have documented a strong causal influence of accurate climate change knowledge on the accuracy of beliefs about climate change (Lewandowsky et al., 2013; van der Linden, Leiserowitz, et al., 2015). Moreover, extensive additional analyses of potential interaction effects (e.g., possible polarization of worldview biases by numeracy) were investigated in many separate analyses, which consistently indicated that all relevant potential interaction effects were statistically trivial and

[3] While the path model was not saturated, one of the best explanations for the observed high fit indices (e.g., RMSEA $= 0$, CFI $= 1$) may be that chi-square of the user model (0.559) is smaller than the degrees of freedom. SRMR, which is not tied to chi-square values, was 0.003.

Table 4
Indirect Effects (Standardized Coefficients) of Key Variables in Study 1

Path	Estimate	*SE*	Bootstrapped 95% CI
Knowledge → belief → risk perception	.36***	.06	[.28, .53]
Numeracy → knowledge → belief	.12**	.05	[.08, .27]
Numeracy → knowledge → risk perception	.04*	.03	[.02, .11]
Numeracy → knowledge → belief → risk perception	.07*	.03	[.04, .17]

Note. Effects were estimated with 5,000 bootstrap samples. *SE* = standard error; CI = confidence interval.
$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

unreliable (see Supplemental Material S1 for the results of linear regression analyses and supplemental analyses).[4] Overall, the findings were consistent with the growing literature documenting a growing number of failures to replicate previously reported evidence of polarization (Ballarini & Sloman, 2017; Maguire et al., 2022; Persson et al., 2021; Shoots-Reinhard et al., 2021).

How Powerful Is Knowledge?

To formally examine the relative predictive power of knowledge and cultural worldviews for beliefs and risk perceptions about climate change, we conducted dominance analysis using Dominance Analysis SAS macro (Azen & Budescu, 2003; Budescu, 1993). Dominance analysis determines relative importance of predictors by computing each predictor's contribution to explaining the variance of the dependent variable in all possible combinations of the predictors. We included expert consensus knowledge and four cultural worldview variables as predictor variables to be compared. Results of the analysis suggested that expert consensus knowledge was the most influential predictor (i.e., general dominance) accounting for 38.20% of the variance in climate change beliefs on average, which was 71.08% of the total variance explained by the regression models. It was followed by egalitarianism and individualism, which explained 7.26% and 5.99% of belief in climate change on average, respectively. When predicting climate change risk perceptions, expert consensus knowledge was again by far the dominant predictor, accounting for 34.47% of the variance in dependent variables, which was about 66.42% of the total explained variance. Again, egalitarianism and individualism were the second and third most influential variables predicting climate change risk perceptions, explaining 8.50% and 7.52% of the variance in risk perceptions (see Supplemental Material S2 for further details; for multiple linear regression analyses and visualizations of predicted probabilities, see Supplemental Materials S3 and S4).

Study 1: Discussion

The results from Study 1 provide the first estimates of the integrated relations linking numeracy, worldviews, and knowledge to climate change beliefs and risk perceptions in a probabilistically representative national sample. Independent of the biases associated with cultural worldviews and other demographic variables, numeracy consistently predicted accurate knowledge, thereby having indirect effects on the accuracy of people's beliefs and the intensity of their risk perceptions (i.e., via differences in their prior knowledge acquisition). Modeling results were also consistent with Skilled Decision Theory and previous research, such that knowledge was found to be by far the single strongest predictor of accurate beliefs and risk perceptions, accounting for more than 5 times the variance in climate change beliefs as compared to cultural worldviews (e.g., a risk literacy Knowledge is Power account). Beyond the strong predictive power of domain-specific knowledge, theoretically, there could be other types of general risk knowledge that have been neglected and that may also be related to risk perceptions. For example, numerate people often acquire more knowledge about many everyday risks faced by society in general

[4] For example, expert consensus knowledge, climate change beliefs, and climate change risk perceptions were regressed on Numeracy × Cultural Worldview interaction terms and main effect of other variables, following the structure of the structural equation model.

(e.g., alcohol, vaccines), which could also result in potentially influential differences in their general risk perceptions (e.g., numerate people may be less concerned about mundane risks than less numerate people, in accordance with expert opinions).

Study 2

Study 2: Method

Previous studies that have examined the relationship between numeracy and climate change risk perceptions have not assessed the role of general risk perceptions, which could meaningfully bear on interpretations of attitudes about climate change (e.g., less numerate people might think climate change is no more worrying than motor vehicles and alcohol use). Therefore, the main goal of Study 2 was to test whether assessing general risk perceptions[5] could help further contextualize the relationship between numeracy and specific climate change risk perceptions. Specifically, in Study 2, we introduced general risk perceptions as a new variable[6] to the integrated model that was developed in Study 1. We then tested this extended model using a convenience sample of diverse adults from the United States in 2020. Study 2 precisely followed the methods and analyses from Study 1, in order to replicate key findings as out-of-sample tests and validation of the model, while also including the novel general risk perception measure in subsequent analyses.

Participants

The data were collected via Amazon Mechanical Turk in March 2020, during the early phases of the COVID-19 pandemic in America. A total of 1,043 responses were collected initially. Out of these, 782 completed at least 90% of all survey items, and 709 out of these 782 participants spent at least 6 min on the survey (e.g., the minimum plausible duration, based on the central tendency of response patterns). Upon launch of the survey, we were notified of an error with two of the questions in the survey (i.e., a response range error). While these were not errors on any of the variables of interest in the present study, we repaired these mistakes and excluded all responses submitted before amending the error, leaving 537 responses, which were used for the analyses.[7] Comparative demographics of the samples in Studies 1 and 2 are presented in Table 5, suggesting the sample was diverse and relatively representative of similar convenience samples of online participants (e.g., slightly younger and more educated as compared to representative samples of U.S. residents).[8] All procedures performed in studies involving human participants were conducted in accordance with all applicable ethical standards and were approved by the institutional review board of the University of Oklahoma.

Measures

All of the same measures from Study 1 were included in Study 2, including (a) statistical numeracy, (b) expert consensus knowledge, (c) belief in AGW, (d) climate change risk perceptions, and (e) cultural worldview. As in Study 1, only two of the three items for fatalism were used in analyses for consistency. Additionally, a new general risk perception instrument was included (Ramasubramanian et al., 2023).

General Risk Perceptions. General risk perception items were assessed using the format developed by Kahan, Landrum, et al. (2017), “How much risk do the following pose for human health, safety, and prosperity?” Questions used a scale from 0 (*no risk at all*) to 7 (*extremely high risk*). The five risks included (a) motor vehicles, (b) skiing, (c) alcohol, (d) nuclear power, and (e) vaccination (for the modified standardized version of the Berlin Risk Perception Inventory, see Ramasubramanian, 2020, 2022; Ramasubramanian et al., 2023). The proportional mean of the five items was compared to the proportional mean of climate change risk perception that ranged from 0 to 10. The Cronbach’s α was .69.

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[5] Here, we use the phrase comparative risk perception to refer to the difference between an individual’s specific risk perception and their general risk perception (i.e., baseline), and comparative risk perception. It is different from *relative risk*, used to often indicate a ratio of probabilities of an event happening between two groups where people in one have been exposed to a treatment, and those in the other not.
[6] For a standardized version of the Berlin Risk Perception Inventory, see Ramasubramanian et al. (2023; Ramasubramanian, 2022).
[7] Including the entire set of responses did not affect the key results (see Supplemental Material S6).
[8] Education was not a significant predictor when included as covariates (see Supplemental Material S7).

Table 5
Correlation Among Variables and Descriptive Statistics

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Perceived risk	7.80	2.16	—													
2. Belief in AGW	7.86	2.29	**.74**	—												
3. Expert consensus knowledge	8.17	1.90	**.61**	**.73**	—											
4. Numeracy	2.88	1.92	−.02	.06	**.13**	—										
5. Individualism	3.60	1.14	**−.21**	**−.25**	**−.23**	**−.23**	—									
6. Egalitarianism	4.28	1.28	**.54**	**.49**	**.37**	−.11	**−.16**	—								
7. Hierarchy	3.35	1.32	−.07	**−.14**	**−.19**	**−.30**	**.63**	−.03	—							
8. Fatalism	3.60	1.15	**.20**	**.15**	.06	**−.23**	**.28**	**.32**	**.40**	—						
9. General risk perception	6.09	1.71	**.26**	**.13**	**.12**	**−.30**	**.20**	**.25**	**.27**	**.28**	—					
10. Skiing	7.44	2.17	**.21**	**.21**	**.23**	.01	−.05	**.17**	.00	.08	. **63**	—				
11. Alcohol	5.83	2.90	**.19**	.08	.08	**−.24**	**.12**	**.21**	**.17**	**.15**	**.75**	**.42**	—			
12. Nuclear power	7.69	2.35	**.37**	**.22**	**.22**	**−.14**	−.03	**.27**	.07	.09	**.69**	**.36**	**.39**	—		
13. Vaccination	3.29	2.93	−.04	**−.13**	**−.16**	**−.33**	**.43**	.03	**.41**	**.35**	**.59**	.09	**.33**	**.14**	—	
14. Motor vehicle	6.20	2.24	**.20**	**.13**	.10	**−.24**	**.11**	**.19**	**.19**	**.23**	**.73**	**.41**	**.34**	**.54**	**.31**	—
15. Comparative risk perception	1.71	2.38	**.72**	**.57**	**.47**	**.20**	**−.33**	**.31**	**−.26**	−.02	**−.48**	**−.37**	**−.16**	**−.26**	**−.34**	**−.27**

Note. When the skewed variable of specific risk perception was transformed to normal distribution, its correlation with numeracy was larger than .30. The bold values represent correlation coefficients significant at $p < .01$. AGW = anthropogenic global warming.

Study 2: Results

Over 90% of participants agreed that there was consensus among experts about AGW ($M = 8.17, SD = 1.90$). Over 90% of respondents also indicated that they believed in AGW ($M = 7.86, SD = 2.29$), revealing that a majority of respondents may already have beliefs consistent with those of experts. The mean climate change risk perception rating was also higher than the scale midpoint ($M = 7.80, SD = 2.16$), indicating a skewed distribution, such that people on average tended to display relatively high-risk perceptions about global warming. As in Study 1, statistical numeracy was significantly correlated with knowledge in expert consensus ($r = .13, p < .01$; see Table 6), although the relation appeared attenuated as a result of the very high base rate of knowledge in Study 2 as compared to Study 1.

Does Statistical Numeracy Predict Enhanced Biases in Climate Change Judgments?

Replication of Study 1: An Integrated Model of Numeracy and Climate Change Judgments. Following the procedure from Study 1, the integrated model was constructed to test the relations between numeracy, worldviews, and knowledge, on downstream climate change beliefs and risk perceptions (see Figure 2). The model fit indices were as follows: $\chi^2(2) = 1.22, p = .54$, with CFI = 1.00, TLI = 1.00, SRMR = $.004$, RMSEA = $.00$ with 90% CI [.00, .07]. As seen in Figure 2, the model again suggested that expert consensus knowledge was by far the strongest predictor of belief in AGW ($\beta = .63, p < .001$), having direct and indirect effects on climate change risk perceptions, which were mediated by beliefs in AGW. Numeracy was again found to predict expert consensus knowledge ($\beta = .13, p < .01$) independent of cultural worldviews and demographic variables (i.e., age, gender). The estimated indirect effects presented in Table 6 suggest that numeracy had significant indirect effects on belief via knowledge. However, the indirect effect to risk perceptions was only significant when knowledge and belief were included as mediators, possibly reflecting complications of the high degree of risk perceptions in the overall sample (e.g., effects attenuated by measurement ceiling; but for clearer estimates, see analyses including general risk perceptions below). Again, potential interaction effects between statistical numeracy and cultural worldview variables were extensively investigated using multiple regression analyses and other modeling and extreme group approaches. All analyses again indicated that interaction effects were consistently unreliable in accordance with Study 1 and the growing literature documenting multiple failures to replicate previously reported evidence of polarization (Ballarini & Sloman, 2017; Maguire et al., 2022; Persson et al., 2021; Shoots-Reinhard et al., 2021; see Supplemental Material S1 for results).

How Powerful Is Knowledge? We again conducted dominance analysis to calculate the relative importance of expert consensus knowledge and four cultural worldviews as predictors of climate change beliefs and climate change risk perceptions. As in Study 1, expert consensus knowledge emerged as the most influential predictor of climate change beliefs, explaining 41.84% of the variance (70.69% of the explained

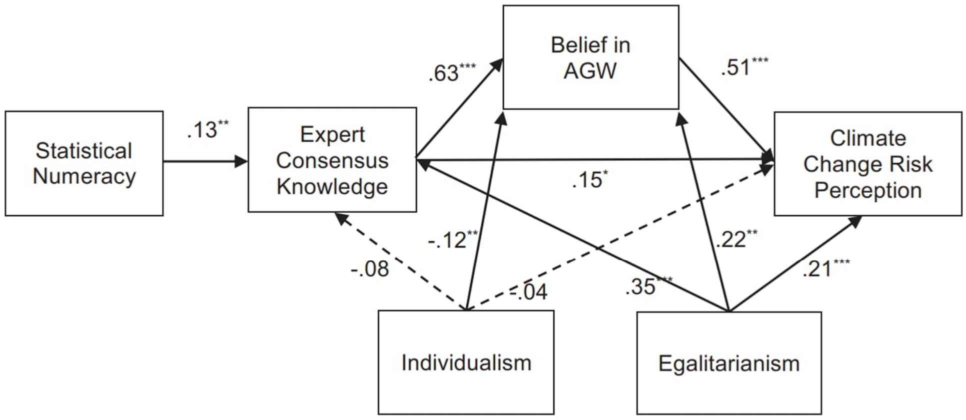
Table 6

Indirect Effects (Standardized Coefficients) of Key Variables in Study 2

Model	Path	Estimate	*SE*	Bootstrap 95% CI
Figure 2	Knowledge → belief → risk perception	.32***	.05	[.26, .46]
	Numeracy → knowledge → belief	.08**	.03	[.03, .16]
	Numeracy → knowledge → risk perception	.02	.01	[.00, .06]
	Numeracy → knowledge → belief → risk perception	.04**	.02	[.01, .08]
Figure 3	Knowledge → belief → climate change risk perception	.32**	.05	[.26, .46]
	Numeracy → knowledge → belief	.08**	.03	[.03, .17]
	Numeracy → knowledge → climate change risk perception	.02	.01	[.00, .05]
	Numeracy → knowledge → belief → climate change risk perception	.04**	.02	[.01, .08]
	Numeracy → general risk perception → climate change risk perception	−.03***	.01	[−.05, −.01]

Note. Effects were estimated with 5,000 bootstrap samples. *SE* = standard error; CI = confidence interval.
** $p < .01$. *** $p < .001$.

Figure 2
An Integrative Model of Numeracy, Knowledge, Beliefs, and Risk Perception



Note. Reported are standardized coefficients after adjusting for age and gender. The representation does not include paths from hierarchy and fatalism, which were as follows: hierarchy → knowledge ($\beta = -.09, p = .09$), hierarchy → belief ($\beta = .04, p = .30$), hierarchy → risk perception ($\beta = .04, p = .20$), fatalism → knowledge ($\beta = .04, p = .37$), fatalism → belief ($\beta = .04, p = .22$), fatalism → risk perception ($\beta = .05, p = .19$). AGW = anthropogenic global warming.
* $p < .05$. ** $p < .01$. *** $p < .001$.

variance), followed by egalitarianism and individualism accounting for 12.83% and 3.03% of the whole variance in climate change beliefs. The same analyses with climate change risk perceptions as a dependent variable revealed that knowledge explained 27.05% of the variance in climate change risk perception on average (54.40% of the predicted variance). Egalitarianism and individualism accounted for 17.60% and 2.37% of the variance (see Supplemental Materials S2 and S5 for more details).

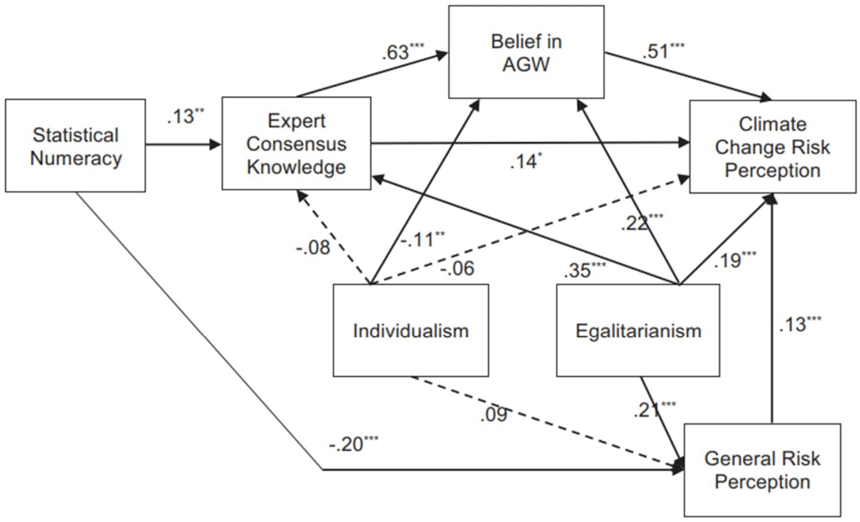
Does Numeracy Predict Comparative Climate Change Risk Perceptions?

Using structural equation modeling, a model with the same structure and covariates (i.e., cultural worldview, demographics) was again tested (Figure 3). Indirect effects were estimated based on 5,000 bootstrap samples (see Table 6). Numeracy was negatively related to general risk perception ($\beta = -.20, p < .001$), suggesting numerate people were less worried about risks in general (e.g., less worried about risks of motor vehicles and skiing). We also found a positive relation between general risk perceptions and specific climate change risk perception ($\beta = .13, p < .001$), suggesting that people who tended to be worried about all risks, in general, tended to be less concerned about climate change specifically (e.g., to some people, climate change is not much more worrying than are motor vehicles). The relations were independent of cultural worldviews and demographic variables. The model fit indices were as follows: $\chi^2(4) = 8.04, p = .09$, with CFI $= 1.00$, TLI $= .97$, SRMR $= .02$, RMSEA $= .04$ with 90% CI [.00, .09].

After controlling for cultural worldviews and demographic variables, the full model produced results that were similar and consistent with all previous models in Studies 1 and 2. Specifically, expert consensus knowledge was again by far the strongest predictor of belief in AGW ($\beta = .63, p < .001$) and had a direct effect on climate change risk perceptions. Numeracy predicted expert consensus knowledge, independent of cultural worldviews and demographic variables ($\beta = .13, p < .01$). However, numeracy was negatively related to general risk perceptions ($\beta = -.20, p < .001$), which in turn was positively related to climate change risk perceptions ($\beta = .13, p < .001$), suggesting numerate people tended to be relatively more worried about climate change as compared to other risks in general (e.g., less numerate people rated motor vehicles as just about as worrying as climate change). General risk perceptions were also found to fully mediate the relationship between numeracy and climate change risk perceptions.

Dominance analysis where expert consensus knowledge and cultural worldviews predicted

Figure 3
A Structural Equation Model With General Risk Perception and Covariates



Note. Reported are standardized coefficients after adjusting for age and gender. The representation does not include paths from hierarchy and fatalism, which were as follows: hierarchy → knowledge ($\beta = -.09$, $p = .09$), hierarchy → belief ($\beta = .04$, $p = .30$), hierarchy → climate change risk perception ($\beta = .02$, $p = .54$), hierarchy → general risk perception ($\beta = .13$, $p < .05$), fatalism → knowledge ($\beta = .04$, $p = .37$), fatalism → belief ($\beta = .04$, $p = .22$), fatalism → climate change risk perception ($\beta = .03$, $p = .33$), fatalism → general risk perception ($\beta = .08$, $p = .06$). AGW = anthropogenic global warming.
$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

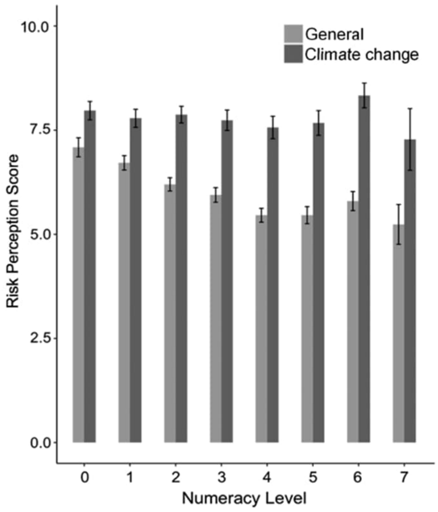
comparative climate change risk perception suggested that knowledge was the most useful predictor, accounting for 15.49% of the variance in comparative climate change risk perception, which was 52.87% of the explained variance. This time individualism and egalitarianism were the next two most influential predictors accounting for 5.43% and 5.31% of the variance, respectively (see Supplemental Material S2 for more details).

Numeracy and Comparative Climate Change Risk Perceptions. To further illustrate the relationship between numeracy and comparative risk perceptions, the average scores for general and climate change risk perceptions were plotted, respectively, with numeracy scores (see Figure 4). As compared to the average risk perception difference, highly numerate individuals tended to have much higher comparative concern for global warming, whereas less numerate individuals were relatively insensitive across risk perceptions (e.g., expressing small differences between general everyday risk perceptions for motor vehicles and climate change risk perceptions).

Study 2: Discussion

All five key findings observed in Study 1 were replicated in Study 2. We found that numeracy predicted more accurate expert consensus knowledge, such that numeracy had direct or indirect effects on the beliefs and risk perceptions independent of cultural worldview biases. Again, knowledge was the strongest predictor of both beliefs and risk perceptions, far exceeding the predictive power of any cultural worldview biases (e.g., individualism, egalitarianism). Furthermore, there was a significant direct correlation between numeracy and comparative risk perceptions in climate change (i.e., climate change risk perception minus general risk perception), with no evidence of judgment polarization. The set of integrated models that included general risk perceptions further revealed that numeracy was negatively related to attitudes about everyday risks in general. In other words, while numerate people were only slightly more concerned about climate change in absolute terms (e.g., as measured by the one climate change risk perception variable), numerate people were

Figure 4
Numeracy and Differences in Risk Perception (Climate Change vs. General)



Note. Average score of everyday general risk perceptions and climate change risk perceptions was plotted across numeracy level. Error bars represent standard errors.

comparatively much more concerned about climate change when compared to other risks faced by society in general (e.g., numerate people rated climate change as far more dangerous than motor vehicles, whereas less numerate people did not).

Measuring General, Specific, and Comparative Risk Perceptions

Beyond the direct effect of domain-specific knowledge (e.g., expert consensus), the present studies reveal that numeracy was also related to differences in general risk perceptions (i.e., as indexed by risk perception ratings for everyday risks including motor vehicles, alcohol, and skiing). These findings are some of the first to suggest that numerate people may typically be less worried about everyday risks to society than less numerate people (e.g., general risk perceptions), which has several methodological and theoretical implications. For example, when comparing the difference between everyday general risk perceptions and climate change risk perceptions, less numerate people rated the risks of climate change as similar to the risks posed by common technologies and activities (i.e., the risk of cars, alcohol, vaccines, nuclear power, and skiing). In contrast, more numerate people were likely to report that climate change was much more worrying than the typical "average" risk faced by society. As such, these results suggest that even when their specific climate change risk perceptions are similar (e.g., rating of 8 of 10), numerate people may be much more worried about the risk of climate change as compared to less numerate people who seem to be generally quite worried about even mundane risks (see Figure 4).

Theoretically, we suspect that the differences observed in general risk perceptions of numerate people are likely to at least partially reflect the fact that, in addition to acquiring more accurate knowledge about climate change in particular, numerate people tend to acquire more accurate knowledge about all kinds of everyday risks more generally. There is much more research that will be needed to understand the primary mechanisms and implications of the observed differences in specific and general risk perceptions. However, going forward, it seems clear that caution is needed when interpreting any individual difference result that focuses only on specific risk perceptions (i.e., climate change risk perceptions). Put simply, failure to measure individual differences in general risk perceptions is a serious potential confound. As such, any individual difference research that fails to control for the effect of general risk perceptions carries a serious risk of biased interpretations (e.g., akin to base rate neglect). To reduce the risk of biased interpretations of findings, researchers should include measures of general risk perceptions, such as the brief (3 min) Berlin Risk Perception Inventory, along with measures of domain-specific knowledge in all future research on the relations between numeracy, beliefs, and specific risk perceptions.

General Discussion

The studies presented here are the first to test an integrated cognitive model of the relations between numeracy, worldviews, knowledge, beliefs, and subjective attitudes about climate change (i.e., specific, general, and comparative climate change risk perceptions). Both studies were conducted with diverse adult residents of the

United States who varied widely or representatively with respect to key variables including skills, worldviews, ages, educations, ethnicities, and gender identities. Consistent with other research conducted over the last 2 decades, we found that a growing majority of U.S. adults agreed about the primary causes and realities of anthropogenic climate change (Leiserowitz et al., 2020; Weber & Stern, 2011). For example, in our probabilistically representative sample of U.S. residents collected in 2016, 84% of participants agreed there was expert consensus on AGW (i.e., answered six or more out of 10; $M = 6.75, SD = 2.55$), and 61% held beliefs consistent with the expert consensus ($M = 6.01, SD = 2.87$). These results converge with others indicating that today a majority of adults in the United States are aware of the strong expert consensus on human-caused global warming and also tend to be concerned about the substantial threat posed by climate change. Unfortunately, not all people understand the current scientific consensus. As a result, many still do not believe in AGW and some also appear relatively unconcerned about the grave risks of climate change for human welfare and society. Nevertheless, the current results indicate that statistical numeracy normally is associated with better understanding and reduced biases (i.e., the risk literacy Knowledge is Power account).

Numerate People Are More Knowledgeable and Knowledge Is Power

There are many reasons for the beliefs and biases people have.[9] However, the single most important factor that generally protects against biased climate change judgments tends to be the accuracy of one's climate change knowledge (e.g., Bord et al., 2000; Lewandowsky et al., 2013; Shi et al., 2015, 2016; Tobler et al., 2012; van der Linden et al., 2018). So, why then are some people so much better informed than others? Consistent with prior findings, results suggest that differences in worldviews are likely to be associated with differences in climate change knowledge acquisition. Indeed, in the present set of studies, individualists were less likely to have previously acquired accurate knowledge about climate change, consistent with theoretical accounts of motivated reasoning processes (e.g., Druckman & McGrath, 2019; Shoots-Reinhard et al., 2021; Tappin et al., 2021; van der Linden et al., 2018). In other words, through the course of their everyday lives, it seems individualists may have generally been motivated to avoid, neglect, or reject at least some relevant knowledge about climate change that conflicted with their prior beliefs, values, and interests.[10]

It is not surprising or novel to find that people with conflicts of interest can have self-serving biases that shape their willingness to consider certain information or specific beliefs. However, the more central question for our current investigation was whether numeracy skills would typically be linked to accurate acquired knowledge, which has been shown to help people avoid climate change biases regardless of their worldviews. As can be seen in the results, our findings unequivocally indicated that numerate people were more likely to have independently acquired more accurate prior knowledge about climate change. In turn, more accurate knowledge was robustly associated with more accurate beliefs and reduced biases in risk perceptions, regardless of people's worldviews or other potential conflicts of interest (e.g., risk literacy Knowledge is Power account; Cokely et al., 2018, 2025). In other words, our findings suggest numeracy is generally unrelated to polarization across objective and subjective climate change judgments, even among individuals with extreme worldviews (e.g., robust linear effects with no evidence of interactions or extreme group polarization).

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[9] People including experts can legitimately disagree about many issues such as religion, free will, personal responsibility, and intentionality (Feltz & Cokely, 2008, 2009, 2012, 2013, 2018, in press; Schulz et al., 2011). As such, for some controversial topics, disagreements are not the result of errors but instead involve differences in moral assumptions and commitments. In these cases, reasonable differences of expert opinion should also give rise to legitimate disagreements among well-informed nonexperts, such as numerate people.

[10] While numeracy appears to generally promote more accurate understanding of risks and thus is linked to reduced belief and attitudinal biases, this does not mean that numerate people should always agree with each other about risks or controversial issues. However, numerate people should generally agree with each other to the extent that there is clear, well-founded expert agreement about the risks. Just as it is common practice for many professional decision makers to consult with multiple expert opinions and to be sensitive to agreement among them (Budescu & Yu, 2006, 2007), numerate people's judgments and choices should also be informed by the strength of expert agreement on various topics.

Limitations

As in all studies, there are some limitations of the current research that should be noted. For one, the present studies do not involve a true experiment, and thus causal mechanisms that may give rise to the results need to be interpreted skillfully. Of course, this concern also applies to all previous studies that involved numeracy because they also could not provide random assignment across relevant independent variables (e.g., different groups were selected on the basis of preexisting individual differences; Kahan, Peters, et al., 2017). Indeed, more generally, previous research suggests it may often be hard to causally differentiate motivated reasoning and other potential sources of biases as factors that contribute to differences in acquired expert consensus knowledge and beliefs (Bago et al., 2023; Tappin et al., 2021).

Second, it is notable that although indirect relations between numeracy, beliefs, and risk perceptions were consistently significant in all structural models, the first-order correlations between statistical numeracy, beliefs, and some climate change risk perceptions were not independently significant (i.e., only significant when controlling for other variables). Nevertheless, as demonstrated in Study 2, which involved the measurement of both general and specific risk perceptions, a significant direct correlation between numeracy and comparative climate change risk perceptions was documented (for a detailed account, see the Study 2: Discussion section).

Third, although the measurements used in the present study appear psychometrically robust and sufficiently sensitive to detect differences in knowledge and beliefs in our adult samples, these assessments were nevertheless very simple (i.e., relied on single questions). Although a single-item measure may be sufficient if the construct being measured is narrow enough, the reliability of a single-item measure will generally tend to be lower (Sackett & Larson, 1990; Wanous et al., 1997). As such, a more precise analysis of the full, multifaceted role of knowledge is likely to require much more extensive assessment, which would ideally be based on validated psychometric instruments including those that are available in the climate change research literature (e.g., see Bord et al., 2000; Shi et al., 2015, 2016; Stevenson et al., 2014; Tobler et al., 2012, for scale measuring knowledge or beliefs about different aspects of climate change). Of note, previous studies suggest that different facets of climate change beliefs and knowledge (e.g., whether it is occurring, its cause, and the severity of its consequences) may often be differentially associated with attitudes or behavioral intentions—a finding that may be quite relevant depending on the aims of subsequent investigations (Benjamin et al., 2017; Broomell et al., 2015; Bruine de Bruin & Morgan, 2019; Heath & Gifford, 2006; Shi et al., 2015).

Fourth, some researchers may prefer other characterizations of some of the measures used in this study. For example, here, an individual's strength of agreement with the existence of an expert consensus in anthropogenic climate change was characterized as *expert consensus knowledge*. The item was designed to differentiate one's personal belief about anthropogenic climate change (i.e., what a person believes) from what one knows about expert consensus (i.e., whether or not one is aware of the expert consensus). We selected this format because, in theory, the item simultaneously assesses both *whether* and *to what extent* one is aware of highly influential external evidence on anthropogenic climate change (e.g., expert consensus). As such, for our purposes, this was useful and efficient given there was clearly an objectively right answer to this question (i.e., experts do agree). However, on other views, this kind of question might perhaps be better characterized as *perceived expert consensus*, since one's response may also involve attitudinal elements (e.g., Goldberg et al., 2022; Lewandowsky et al., 2013). Accordingly, it may be prudent for future research to select multiple measures for key variables, preferably including psychometrically validated scales and instruments if available.

Last, although we used one relatively high-quality sample and another larger sample of diverse adult decision makers, the sample sizes in both our present studies were smaller (i.e., 30%–50% as large) than that used in the previous study where the motivated numeracy effect was originally observed (Kahan, Peters, et al., 2017; $n = 1{,}111$). While this smaller sample could theoretically be a factor, from our perspective, it would seem unlikely to cause any meaningful difference considering the use of more refined measures of the cultural worldviews in the present studies (i.e., did not require extreme groups analysis based on a small subsample of participants) and given our general and extensive approach to modeling (e.g., structural modeling with 5,000 resampling bootstrap estimates). Moreover, it is notable the motivated numeracy effect has also failed to be replicated in a study that used a much larger sample size, conducted by Persson et al. (2021; $n = 3{,}154$).

Conclusions

Taken altogether, in light of all available research, we find there is no compelling evidence generally linking numeracy to increased biases or polarization in beliefs and risk perceptions about climate change. In contrast, there is good reason to generally expect to find the opposite. For example, the estimated unique association between numeracy and accurate climate change knowledge in the present set of studies was roughly 3 times larger than the estimated magnitude of the unreplicated polarization effect between numeracy and subjective attitudes that was observed in a small subsample of participants in prior research (Kahan et al., 2012; also see Ballarini & Sloman, 2017; Maguire et al., 2022; Persson et al., 2021; Stagnaro et al., 2023, for failure of replications; see Supplemental Material S8 for effect size comparisons). To the extent, the current findings generalize, numeracy can be expected to predict people's independent acquisition of more accurate knowledge about most risks in general, including controversial risks. In other words, the current results are consistent with the risk literacy Knowledge is Power account: When people have the skills to accurately evaluate and understand the risks, they are much more likely to become more informed and less biased reasoners, regardless of potential controversies and conflicts of interest.

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