Title

Understanding and Shaping Trust in Science

ISBN

9798180117755

Author

Chaplin, Kayla Marie

Publication Date

2026-05-27

UNIVERSITY OF CALIFORNIA
RIVERSIDE

Understanding and Shaping Trust in Science

A Dissertation submitted in partial satisfaction
of the requirements for the degree of

Doctor in Philosophy

in

Psychology

by

Kayla Marie Chaplin

June 2026

Dissertation Committee:
Dr. Jimmy Calanchini, Chairperson
Dr. Kate Sweeny
Dr. Stephen Antonoplis

The Dissertation of Kayla Marie Chaplin is approved:

Committee Chairperson

University of California, Riverside

Acknowledgments

First, I would like to thank my advisor, mentor, and chair of my dissertation committee, Jimmy. Thank you for your guidance and dedication to my educational experience. I cannot express how much your unwavering support means to me.

I would also like to thank my other dissertation committee members, Kate and Stephen. I appreciate all the thoughts and insight both of you contributed to make my dissertation stronger.

Next, I would like to thank the Science to Policy program. Thank you for changing my life and making me a better researcher, science communicator, and human.

I would also like to thank my lab mates for all their support. To my older lab mate sisters, you were a huge support system for me and helped me learn the ways of grad school, research, and life. To my younger lab mate sisters, watching and helping you grow has made me grow in my own ways, and I'm so excited to see you all succeed.

Finally, I would like to thank my friends, family, and partner. To my friends inside and outside of academia, thank you for always supporting me, whether it was a shoulder to cry on, an ear to listen, or an understanding of why I never texted back. To my family, thank you for your support, for always asking me questions, and for continuing to tell me how proud you are. To my partner who has been with me since I wanted to be in grad school, thank you for supporting me in every way possible, for letting me practice my talks or read a sentence out loud, and for always making me laugh when I felt like my world was falling apart. All of you, and many unmentioned, made this possible for me.

ABSTRACT OF THE DISSERTATION

Understanding and Shaping Trust in Science

by

Kayla Marie Chaplin

Doctor of Philosophy, Graduate Program in Psychology
University of California, Riverside, June 2026
Dr. Jimmy Calanchini, Chairperson

Trust in science has important implications for health behavior and policy support, yet most research relies on explicit measures that are vulnerable to social desirability. Based on dual-process theory, this dissertation first establishes the predictive validity of implicit and explicit measures of trust in science on science-related behavior. Building on the foundation of understanding of implicit and explicit trust in science, this dissertation also aims to understand how message framing, uncertainty, and scientific knowledge shape implicit and explicit trust in science and behavior. In Experiment 1, I measured implicit trust in science using a single-category IAT, explicit trust using self-report measures, and behavior using scientific news headline choices. In Experiment 2, I manipulated how science is framed – static (science as fixed) versus dynamic (science as evolving) – and tested if scientific knowledge moderates the effect on implicit and explicit trust. In Experiment 3, I examined the joint effect of high versus low uncertainty with the same framing and scientific knowledge from Experiment 2. I also included exploratory analyses looking at how demographic variables such as political identity, religion, and education, relate to all factors across the three experiments. Finally, I ran a mini meta-analysis looking at effects across the three experiments. The results support that implicit trust in science is a distinct process from explicit trust in science and that both can be impacted by the framing manipulation. While uncertainty did not directly impact trust in science, the results from Experiment 3 show how scientific knowledge buffers against the negative effects high uncertainty has on explicit trust in science. Implicit and explicit trust in science consistently differ across political identity and religion in important ways. Overall, this dissertation moves beyond self-report alone to provide a more complete picture of how trust in science is formed and acted upon. The results contribute to a growing field of science aiming to improve the public's trust in science.

Keywords: Trust in science, implicit trust, science communication, message framing, scientific uncertainty, dual-process theory

Table of Contents

List of Tables

List of Figures

Understanding and Shaping Trust in Science

We live in a world where people trust astrology more than astronomy, influencers more than immunologists, and conspiracy theories more than climate science. Despite scientific advancements shaping nearly every aspect of modern life, public trust in science continues to decline (Kennedy & Tyson, 2023), presenting significant challenges for scientists, policymakers, and public health experts who rely on the public's willingness to accept and act on scientific knowledge. At the heart of these challenges lies trust, a cognitive process that influences how people evaluate information and make decisions (Hertzberg, 1988; Voas, 2014).

Trust in science is not simply a matter of whether people know scientific facts or endorse science in general. Understanding trust in science therefore requires examining not only how much people explicitly report trusting science, but also how people automatically associate science with trustworthiness and how communication and uncertainty shapes those evaluations. Across three experiments, I examine whether implicit and explicit trust in science reflect distinct processes, whether these processes predict science-related behavior, and how these distinct processes of trust in science are shaped by science communication, scientific uncertainty, and scientific knowledge. By integrating implicit, explicit, and behavioral measures, this dissertation aims to provide a more complete understanding of how trust in science is formed, expressed, acted upon, and shaped.

Trust in Science

Trust develops through observation and leads people to believe that others' actions are dependable (Jones, 2002); this belief shapes how we form intentions and expectations in our interactions with others (Wisniewski et al., 2024). Whether people trust or distrust others fundamentally influences other cognitive processes, such as affecting how information is interpreted and integrated (Mayo, 2015). In addition, trust and distrust guide social evaluations of others (Todorov et al., 2009). While trust commonly applies to interpersonal relationships, it also operates at the institutional level, such that trust in systems or authorities differs conceptually from trust between individuals (Luhmann, 1979). Institutional trust becomes particularly important in contexts where direct personal experience with the institution is limited or impractical, prompting reliance on perceived expertise, reliability, and good intentions of institutional representatives (Hall et al., 2001). Science is a prime example of such institutional trust.

Within the specific context of science, trust reflects how people evaluate scientists, scientific institutions, and scientific knowledge itself (Sztompka, 2007). Low trust in science has significant behavioral consequences: people who have lower trust in scientific institutions are less likely to adhere to health recommendations (Borinca et al., 2024), more likely to respond negatively to public health messages (Plohl & Musil, 2023), and more susceptible to misinformation, particularly through social media (Lee et al., 2023). Moreover, lower trust in science contributes to resistance against science-based policymaking and promotes disengagement from constructive scientific discourse

(Guidotti, 2017). Given the consequences of low trust in science, understanding how trust can be shaped is imperative.

Trust in science is often measured through direct self-report, which may only be capturing one aspect of how people trust science. People may be able to deliberately report how much they trust science, scientists, or scientific institutions, but these reports may not fully capture the gut-level trust, or automatic associations between trust and science. Therefore, my dissertation draws from dual-process perspectives to examine trust in science as involving both explicit and implicit cognitive evaluation processes.

Measuring Trust in Science

Most studies thus far rely on explicit measures, such as surveys asking people to reflect on how much they trust science or scientists. While these measures provide valuable insights, explicit measures are also vulnerable to social desirability bias, especially in contexts where people may be motivated to appear pro-social, unbiased, or supportive of science (Fisher, 1993; Furnham, 1986; Krumpal & Voss, 2020), such as taking part in a scientific survey. Trust may be influenced by social expectations from both interpersonal interactions (Wei et al., 2019) and institutional social processes (Jagd & Fuglsang, 2016), suggesting that explicit trust in science measures may reflect not only personal beliefs but also external pressures to align with social groups or institutions. As a result, there is a growing need for alternative approaches to capture people's trust in science (Besley & Tiffany, 2023).

To address the limitations of explicit measures, researchers in cognitive and social psychology developed implicit measures that do not rely on direct self-report. Consistent with dual-process theories, implicit and explicit measures differ in the underlying principles that guide them. Implicit attitudes are grounded in associative processes, or automatic pairings of concepts, while explicit attitudes are guided by propositional reasoning, or the evaluation of whether a belief is accurate or valid (Gawronski & Bodenhausen, 2006, 2009). As a result, people may form implicit associations (e.g., between trust and science) that persist even when they consciously reject the logic or truth of the relationship. Empirical research supports this dissociation: implicit measures often reflect automatic associations, while explicit measures reflect deliberate judgments shaped by social norms and reasoning (Fazio & Olson, 2003; Fazio & Olson, 2014; Rydell et al., 2006).

Dual-process theories explain the gap between implicit and explicit responses: attitudes and behaviors stem from both automatic and controlled systems (Chaiken & Trope, 1999). The automatic route relies on quick associative activations that guide behavior without deliberation, whereas the controlled route involves intentional reasoning before acting (Ajzen, 1991; Fazio, 1990; Gawronski & Creighton, 2013). Whether behavior is guided by one route or the other depends on a person's motivation and opportunity to process information. Under low motivation or limited cognitive resources, behavior tends to follow automatically activated associations. When motivation and opportunity are high, people are more likely to reflect and adjust their responses, particularly in ways that conform to perceived social norms (Ajzen & Fishbein, 1980; Fisher, 1993; Hofmann et al., 2008). Moreover, control resources also moderate whether automatic or controlled processes guide behavior, with explicit measures being more predictive under full cognitive capacity than under conditions of memory load (Hofmann et al., 2008).

Implicit measures, such as speeded categorization and subliminal priming tasks, are designed to capture automatic responses that are more difficult to intentionally control (Fazio & Olson, 2003; Greenwald et al., 1998). For example, the Implicit Association Test (IAT) is a speeded task in which people repeatedly categorize positive and negative words paired with social targets, providing insight into their underlying associations (Greenwald et al., 1998). These methods have been widely used to examine attitudes across a range of domains, including racial bias (Greenwald et al., 1998), personality (Schnabel et al., 2006), self-esteem (Greenwald & Farnham, 2000), and political preferences (Nosek et al., 2002). Furthermore, research on general trust has increasingly used implicit measures to explore automatic judgments of trustworthiness. For example, trust has been assessed implicitly in domains such as safety culture (Burns et al., 2006), social networks (Yadav et al., 2015), recommender systems (Guo et al., 2014), and government trust (Intawan & Nicholson, 2018).

Implicit and explicit measures often diverge and do not correlate strongly (Fazeli et al., 2014; Merritt et al., 2013), suggesting that each measure offers unique predictive validity. Despite growing calls for moving beyond self-report in trust in science research (Besley & Tiffany, 2023), implicit measures remain underused. One notable exception used two IATs to gauge students' implicit associations between science and utility/trustworthiness; the implicit measure scores predicted science knowledge beyond explicit measures, supporting implicit trust in science as a distinct construct (Schoor & Schütz, 2021).

Although implicit measures were initially developed to minimize social desirability and increase validity, the divergence between implicit and explicit responses cannot be attributed solely to lack of awareness. Several factors, such as representational strength, processing awareness, and contextual cues, influence the relationship between implicit and explicit responses (Hofmann et al., 2005). Implicit and explicit responses often diverge when people are under cognitive load or otherwise unable to engage in effortful reflection. In such situations, responses are more likely to be driven by the automatic associations, which is the underlying mechanism reflected in implicit measures (Smith & Collins, 2009).

Motivational factors also shape the relationship between implicit and explicit responses. For example, deliberate reasoning can reduce implicit-explicit correspondence (Phillips & Olsen, 2014). Impression management and self-deceptive enhancement complicate the interpretation of explicit evaluations, particularly in domains where social pressure to appear unbiased is high (Bou Malham & Saucier, 2016). Further supporting this, Nosek (2007) found that implicit-explicit correlations tend to be stronger in less socially sensitive domains (e.g., abortion) and weaker in more socially sensitive ones (e.g., race), suggesting that divergences between implicit and explicit measures often reflect psychologically and contextually meaningful processes rather than error.

Rather than being redundant, implicit and explicit measures offer complementary insights by capturing distinct cognitive processes shaped by different motivational and contextual conditions. Divergences between the two measures reflect meaningful psychological patterns that unfold across both automatic and controlled systems (Gawronski & Bodenhausen, 2006, 2009). Because implicit measures are less susceptible to social desirability and self-presentation concerns, they may provide insights into underlying associations under certain conditions (O'Shea, 2018). In many cases, implicit measures also outperform explicit in predicting behavior (Greenwald et al., 2009). For example, general implicit trust has been shown to predict behavior beyond what is explained by explicit trust (Merritt et al., 2013), reinforcing the value of using both types of measures to understand how trust in science shapes real-world decision-making.

Taken together, the literature suggests that trust in science may involve multiple cognitive evaluation processes. Explicit measures provide insight into people's deliberate evaluations of science and scientists, whereas implicit measures may capture more automatic associations between science and trustworthiness. The present dissertation builds on the existing dual-process literature by examining whether implicit and explicit trust in science relate differently to science-related behavior and whether these forms of trust are shaped differently by communication framing and uncertainty.

Framing in Science Communication

If trust in science involves multiple cognitive evaluation processes, then the way science is communicated may shape those processes differently. Social psychologists have shown that message framing strongly shapes attitudes and behavior. For example, framing information as part of a changing trend (i.e., dynamic norm framing) is more effective at changing behavior than framing information as stable or typical (static norm framing) (Ma & Reynolds-Tylus, 2024; Sparkman & Walton, 2017). Similarly, research on trust in science finds that communication style powerfully affects public trust (Intemann, 2023). Just as framing influences general attitudes and behavior, the way scientific information is framed can affect whether people view science as trustworthy. For example, communicating how the scientific process works fosters more trust in science in some settings, but decays trust in science in other settings (Kreps & Kriner, 2020). In response to concerns about declining trust, critics have called on scientists to improve their public communication practices. Increased transparency and openness about scientific practices may increase trust (Grand et al., 2012), though some academics have argued that the current structure of science communication often reinforces public skepticism and disconnect (Irwin & Horst, 2016).

Integrating insights from social psychology and trust in science research suggests that framing science as dynamic, rather than static, may have an influence on trust in science. A dynamic framing of science emphasizes that scientific knowledge changes over time as new evidence emerges, whereas a static framing of science emphasizes stable facts and enduring conclusions. While the dynamic framing of science aligns with the actual process of the scientific method, the static framing emphasizes certainty and confidence in scientific findings, which likely leads to more trust in science. Understanding these framing effects is crucial, as it highlights how strategic communication choices can either strengthen or weaken public trust in science.

Uncertainty in Science

Scientific uncertainty is built into research, yet the way scientists convey that uncertainty can strengthen or weaken public trust. While transparency about uncertainty in science can increase perceived honesty and reduce communicator bias (Steijaert et al., 2020), it may also be exploited by skeptics or misinterpreted by the public (Hendriks & Jucks, 2020). The way uncertainty is presented can affect how people understand scientific information (Budescu et al., 2009; Corbett & Durfee, 2004); people's reactions to uncertainty depend on several factors, including the type of uncertainty conveyed (Gustafson & Rice, 2020). For example, highlighting uncertainty about *when* climate-related threats will happen, rather than uncertainty about *what* exactly will happen, led people to view those threats as more serious and motivated them to support actions (Ballard & Lewandowsky, 2015). In addition, individual-level factors like prior beliefs about science or political orientation also impact how uncertainty affects trust in science (Rabinovich & Morton, 2012).

Trust in science is a critical issue during times of uncertainty, such as during the COVID-19 pandemic. In the beginning of the COVID-19 pandemic, trust in science increased initially but declined over time, with partisan differences emerging (Bromme et al., 2022; Hatton et al., 2022). During this uncertain period, how science was communicated eroded public trust in some contexts (Kreps & Kriner, 2020; van der Bles et al., 2020). Furthermore, the changing nature of scientific knowledge was highlighted during the pandemic, challenging the public's understanding of science (Sotério, 2021).

Taken together, it is critical to understand how scientific knowledge interacts with communication framing and uncertainty to affect people's trust in science. Uncertainty does not necessarily affect trust in science uniformly. Instead, people may interpret uncertainty through their existing understanding of science, prior beliefs, and broader social identities. Therefore, my dissertation examines uncertainty not simply as a factor that lowers trust, but as a contextual feature that people interpret differently depending how science is being communicated and on their understanding of science. This distinction is important because it shifts the focus from whether uncertainty is good or bad for trust to when and for whom uncertainty shapes trust in science.

Scientific Knowledge

An important factor that may moderate both framing communication and uncertainty is a person's knowledge of scientific information. Trust in science is associated with greater vaccine confidence and compliance with health guidelines (Bicchieri et al., 2021; Sturgis et al., 2021), however, this relationship is moderated by individuals' scientific understanding. Moreover, people with better scientific reasoning skills and higher trust in science tend to have fewer conspiracy beliefs and are more likely to follow evidence-based recommendations (Čavojová et al., 2023).

Importantly, understanding how science works may matter more than memorizing facts. Rather than focusing on the content of science, it is more crucial to consider the public's understanding of how scientific knowledge is produced and what kinds of questions science can realistically address (Millar & Wynne, 1988). When the public has a better understanding of science as a process, they are more likely to trust science (Slater et al., 2019). Trust in science also increases when people understand how scientific knowledge is formed and which sources are trustworthy (Sinatra & Hofer, 2016). Furthermore, people with high trust in science are better able to evaluate the quality of scientific studies, protecting them from low-quality evidence (Rosman & Grösser, 2023). Taken together, it is critical to understand how scientific knowledge interacts with science communication and uncertainty to affect people's trust in science.

In my dissertation, I distinguish between objective scientific knowledge and the skills people have required for the scientific process. Objective scientific knowledge refers to correct answers on questions about scientific concepts or methods. Science process skills refer to people's perceived ability to engage with scientific inquiry, evaluate evidence, and understand how scientific knowledge develops. This distinction is important because people may know scientific facts without fully understanding scientific revision, uncertainty, or evidence accumulation. Taken together, research on science communication, uncertainty, and scientific understanding suggests that trust in science is shaped not only by what information people receive, but also by how people interpret that information. Therefore in my dissertation, I examine the moderating effect of objective scientific knowledge and scientific process skills.

Present Study

The goal of my dissertation is to address three key questions: (1) Do implicit and explicit trust in science reflect distinct cognitive processes that predict science-related choices? (2) How do static (fixed) versus dynamic (evolving) communication messages influence implicit and explicit trust and science-related behavior, and does scientific knowledge play a moderating role? and (3) How does uncertainty interact with static versus dynamic communication messages and scientific knowledge to influence implicit and explicit trust and science-related behavior?

In Experiment 1, I will establish a foundation by testing whether implicit and explicit trust in science uniquely predict science-related behavior. Participants will complete an implicit measure of trust in science, explicit measures of trust in science and trust in scientists, and a behavioral science article selection task. I hypothesize that implicit measures of trust in science will be a stronger predictor of behavior compared to explicit measures of trust in science.

In Experiment 2, I will examine whether communication framing shapes implicit and explicit trust in science and science-related behavior. I will manipulate message framing to be static or dynamic and look at scientific knowledge to see how both factors influence trust in science and behavior. I hypothesize that scientific knowledge will moderate the effect of science framing on trust in science. Specifically, I hypothesize that people with lower scientific knowledge will have more trust in science when exposed to static framing. In contrast, people with higher knowledge may either have more trust in science when exposed to dynamic framing, or their trust in science may not be affected by the framing.

Experiment 3 extends Experiment 2 by examining how scientific uncertainty interacts with framing and scientific knowledge. In Experiment 3, I will manipulate scientific uncertainty (high vs. low) in combination with the same static versus dynamic framing from Experiment 2 and look at their joint impact on trust. I hypothesize that high uncertainty will lower trust in science overall, particularly for participants in the dynamic condition. However, participants with higher scientific knowledge may show either higher or more stable trust in science across uncertainty conditions, buffering against the effects of uncertainty and dynamic framing. Furthermore, I hypothesize that participants with lower scientific knowledge will show the lowest trust in science under conditions of high uncertainty and dynamic framing. For Experiments 2 and 3, I do not have strong hypotheses for how implicit and explicit trust in science, or how the behavioral measure, will differ in response to framing and uncertainty manipulations.

I will also run exploratory analyses to explore (1) the validity and reliability of the measures used in all experiments given that some of the measures are novel (2) if demographic factors such as political identity, religious beliefs, and education relate to people's implicit and explicit trust in science and science-related behavior and (3) the overall effects in a mini-meta analysis to establish consistency across the three experiments. Because these analyses are exploratory, I do not have hypotheses for these effects.

Together, my dissertation aims to contribute to psychological research by providing a clearer understanding of the cognitive processes involved in trust in science and how these processes respond to communication framing and uncertainty. By integrating implicit, explicit, and behavioral measures, this work offers a more complete picture of how people evaluate science and when different types of trust in science may be strengthened or weakened. Beyond contributing to the psychological literature, this dissertation also has real-world implications for rebuilding trust in science.

Understanding how people hold different types of trust in science and how their trust responds to science communication and uncertainty can inform future research in science communication interventions, contextual influences on trust, and science policy more broadly.

Experiment 1

Experiment 1 establishes a foundational understanding of how implicit and explicit trust in science relates to people's choice behaviors. Specifically, this experiment assesses whether implicit and explicit measures of trust differently predict what kind of scientific news articles people choose to read. Experiment 1 aims to provide insight into the cognitive processes underlying trust in science and how this in turn affects how people choose scientific information.

Methods

Participants

I conducted an a priori power analysis using G*Power (Faul et al., 2007) to determine the minimum required sample size for a linear regression model predicting behavioral trust from two predictors: implicit trust and explicit trust. Using a medium effect size ($f^2 = 0.15$), a significance level of $\alpha = .05$, and a desired power of 0.80, the analysis indicated that a total sample size of 43 participants would be required to detect a significant effect of either predictor.

I collected data from a total of 110 participants. As laid out in my pre-registration, I excluded participants if they: (a) failed the embedded attention check item ($n = 11$), (b) met the single-category IAT exclusion criteria (fewer than 50% correct or more than 10%

of trials with reaction times under 300 ms; $n = 3$); or (c) had missing data on a primary dependent variable ($n = 0$). The final sample consisted of $N = 96$ participants (45 men, 50 women, 1 trans-woman) recruited via CloudResearch Connect. The mean age was 44.51 years ($SD = 15.48$, range 18-73). The majority identified as non-Hispanic or Latino/a (83.5%). Approximately 48% identified with the Democratic Party and 24% with the Republican Party. Most participants completed at least some college (72%), and about half identified as Christian (48.5%), while 26% identified as non-religious (atheist or agnostic). Full sample characteristics are presented in Table 1. I identified three additional participants as outliers (more than 3 *SD*s from the mean on at least one primary dependent variable) and excluded them from sensitivity analyses, yielding $N = 93$ for those models.

Table 1
Experiment 1 Sample Characteristics

	Characteristic	*n*	%
Gender	Man	45	46.4%
	Woman	50	51.5%
	Trans-Woman	1	1.0%
Ethnicity	Hispanic or Latino/a	15	15.5%
	Not Hispanic or Latino/a	81	83.5%
Education	High school diploma	7	7.2%
	Associate's degree	18	18.6%
	Some college	18	18.6%
	Bachelor's degree	30	30.9%
	Master's degree	19	19.6%
	Doctorate degree	3	3.1%
	Professional degree	1	1.0%
Political party	Democratic Party	46	47.9%
	Republican Party	23	24.0%
	Independent	14	14.6%
	Libertarian Party	3	3.1%
	Green Party	2	2.1%
	No party affiliation	6	6.3%
	Other	2	2.1%
Political views	Very liberal	13	13.5%
	Liberal	26	27.1%
	Slightly liberal	12	12.5%
	Moderate	10	10.4%
	Slightly conservative	4	4.2%
	Conservative	15	15.6%
	Very conservative	8	8.3%
	Do not identify	8	8.3%
Religion	Christian	47	48.5%
	Agnostic	14	14.4%
	Atheist	11	11.3%
	No religion	14	14.4%
	Jewish	5	5.2%
	Not listed / prefer not	5	5.2%
Continuous variables	Age	$M = 44.51$, $SD = 15.48$, range 18-73	
	Political interest (1-7)	$M = 5.07$, $SD = 1.73$	

Note. $N = 98$.

Design

For Experiment 1, I implemented a within-subjects design, where participants completed measures of implicit and explicit trust in science, followed by a behavioral choice task assessing science-related information selection. I assessed explicit trust in science using two measures; one designed to align directly with the implicit measure – using the same conceptual words – and one measuring trust in scientists more broadly in four dimensions (competence, integrity, benevolence, openness). This design allowed for direct comparison of implicit and explicit trust in science measures within individuals to examine their relative influence on science-related behavioral choices.

Materials

Implicit Association Test. Participants completed a single-category IAT (SC-IAT: Karpinski & Steinman, 2006), a dual-categorization task that consists of stimuli related to two attribute categories (trustworthy and suspicious words) and stimuli related to one target category (science pictures) (see Table 2 for the stimuli list). Stimuli appeared on the computer screen one at a time, and I instructed participants to categorize each with one of two response keys. In one critical block of SC-IAT trials, science target pictures shared one response key with trustworthy words, and the other response key was only suspicious words. In the other critical block of IAT trials, the pairings were switched such that science target pictures shared one response key with suspicious words, and the other response key was only trustworthy words. I randomized the order in which pairing participants saw first. I scored SC-IAT performance in terms of the *D*-score (Greenwald et al., 2003), which reflects the difference in standardized response latencies between the two critical blocks, such that faster responses when science shares a response key with trustworthy versus suspicious words suggest more trust in science. I pretested all trustworthy words, suspicious words, and science target pictures in a separate sample of CloudConnect participants to ensure high construct validity (see Supplemental Materials for all pretest details).

Table 2

Stimuli for Single-Category Implicit Association Test

Target: **Science**	
Attribute: **Trustworthy**	Honest, Good, True, Decent, Loyal, Steady, Fair, Reliable, Solid, Genuine, Dependable, Valid, Sincere, Secure, Credible, Ethical, Accurate, Respectable
Attribute: **Suspicious**	Bad, Phony, Sketchy, Shady, Fishy, Lying, Sneaky, False, Fake, Foul, Corrupt, Dirty, Wrong, Suspect, Questionable, Dicey, Shaky, Fraud

Explicit Science Trust-Suspicion Scale. Participants completed a self-report scale assessing explicit trust in science that I designed to align conceptually with the implicit trust measure. Participants rated how much they agreed or disagreed with 36 statements using a 7-point Likert scale ranging from 1 (Strongly Disagree) to 7 (Strongly Agree). The instructions prompt read: "Please indicate how much you agree or disagree with the following statements about science." On the rating pages, the text read, "I consider science to be…" followed by one of 36 words I used as stimuli in the SC-IAT to assess trust versus suspicion of science (Table 2). I reverse-scored suspicious items prior to computing the explicit trust score, such that higher scores reflect greater overall trust in science.

Explicit 4-Dimensional Trust in Scientists Measure. Participants completed a 12-item self-report scale assessing explicit trust in scientists in four different dimensions: competence, integrity, benevolence, openness (Besley & Tiffany, 2023; Cologna et al., 2025). For each dimension, participants responded to three questions. For competence, an example item is, "How qualified or unqualified are most scientists when it comes to conducting high-quality research?" For integrity, an example item is, "How honest or dishonest are most scientists?" For benevolence, an example item is, "How concerned or not concerned are most scientists about people's well-being?" For openness, an example item is, "How willing or unwilling are most scientists to be transparent?" Participants rated each item using a 5-point Likert scale with 1 being "very [unqualified; dishonest; unconcerned; unwilling]" to 5 being "very [qualified; honest; concerned; willing]." The scale used the phrasing appropriate for each of the 12 items. Higher scores reflect greater trust in scientists within each category; I also computed an overall score.

Objective Scientific Knowledge Measure. Participants completed nine questions from a quiz-style measure assessing understanding of the scientific process. I retrieved the questions from an intro to psychology methods course. Questions were all multiple choice and only had one correct option. An example item is, "What is one reason that causal claims cannot be made from correlational studies? A) participants are randomly assigned to groups B) correlations are not sensitive enough to detect causal associations C) the temporal order of the correlated variables is not always known D) correlational studies only involve a single variable."

Science Process Skills Inventory. Participants completed an 11-item survey (Arnold et al., 2013) assessing their ability to engage in scientific inquiry, using a 4-point scale ranging from *Never* to *Always*. An example item includes, "I can design a scientific procedure to answer a question."

Filler Tasks. Participants completed three filler task measures: (1) the 6-item Need for Cognition Scale (NFC: Coelho et al., 2018), which assesses enjoyment of effortful thinking, (2) the Positive and Negative Affect Schedule (PANAS: Watson et al., 1988), a 20-item mood measure evaluating positive and negative affect over the past few days, and (3) the Big Five Inventory-10 (BFI-10: Rammstedt & John, 2007), which assesses personality traits. The purpose of the filler task was to collect additional individual difference data that may be relevant for exploratory analyses and to serve as a brief filler task between the trust measures and the behavioral choice task. While participants may have still discerned the general aim of the experiment, the inclusion of these measures acted as a precautionary step to reduce immediate demand characteristics and increase the psychological separation between predictor and outcome variables.

News Article Selection Task. Participants saw 16 fake news article headlines and I instructed them to choose 5 articles. Specifically, the instructions read, “Please select 5 News Articles you would like to read further. You will need to answer questions about the articles, so please choose articles you find CREDIBLE and INTERESTING.” I adapted the task from prior selective exposure paradigms designed to examine information preferences (Knobloch-Westerwick & Meng, 2009; Panek, 2016). I pretested the headlines in a CloudConnect sample and selected the 16 article pairings that had the widest scientifically-rated gap (high scientific rating for the scientific article and low scientific rating for the non-scientific article; see Supplemental Materials). This gave me a total of 32 news article headlines that focused on science-related topics (e.g., “Neuroscientists Explore How to Cure Your Fear of Flying”), while the other half presented non-scientific versions of the same topics (e.g., “Pilots Talk About How to Cure Your Fear of Flying”) (see Table 3 for all topics). I coded the experiment to present the headline topics in the same order for all participants but randomly show participants either the scientific version or the non-scientific version, with a 50% distribution of scientific and non-scientific articles shown for each participant. For example, one participant saw, “Scientists Study How Coffee Affects Focus in ADHD Brains” first and “Parents Pinpoint Phones as the Cause of Sleepless Nights” second, and another participant saw, “Influencer Opens Up on How Coffee Affects Focus in ADHD Brains” first and “Scientists Pinpoint Phones as the Cause of Sleepless Nights” second. This task assessed participants’ preference for science-related information by comparing the proportion of science and non-scientific related article choices.

Table 3

Articles for Behavioral Measure

Scientific Headlines	*Non-Scientific Headlines*
Scientists Study How Coffee Affects Focus in ADHD Brains	Influencer Opens Up on How Coffee Affects Focus in ADHD Brains
Scientists Pinpoint Phones as the Cause of Sleepless Nights	Parents Pinpoint Phones as the Cause of Sleepless Nights
Brain Researchers Link Stress to Poor Memory Throughout the Day	Workers Say Stress Links to Poor Memory Throughout the Day
Climate Scientists Report Sudden Shift in Ocean Currents	Fishing Crews Notice Sudden Shift in Ocean Currents
Neuroscientists Explore How to Cure Your Fear of Flying	Pilots Talk About How to Cure Your Fear of Flying
Scientists Develop Cheaper, More Efficient Solar Panels	Homeowners Install Cheaper, More Efficient Solar Panels
Geologists Discover Why Landslides Are Becoming More Common	Hill-Side Homeowners Consider Why Landslides Are Becoming More Common
Scientists Are Researching the Benefits of Fiber for Overall Health	Health Influencers Are Talking About the Benefits of Fiber for Overall Health
Researchers Discover Cause of Rising Food Allergies	Parents Talk About Cause of Rising Food Allergies
Zoologists Discover How Pets Boost Our Immune Systems	Pet Owners Talk About How Pets Boost Our Immune Systems
Psychologists Find Music Boosts Mood Quickly	Music Lovers Say Favorite Songs Boosts Mood Quickly
Geneticists Unlock Answers to Sudden Hair Loss	Hair Stylists Unlock Answers to Sudden Hair Loss
Plant Biologists Report What You Can Add to Soil to Save Your Houseplants	Gardening Enthusiasts Detail What You Can Add to Soil to Save Your Houseplants
Scientists Create Robot Hand That Feels Like Human Touch	Tech YouTubers Test Robot Hand That Feels Like Human Touch
Researchers Study How Social Media Shortens Attention Spans	Teens Talk About How Social Media Shortens Their Attention Span
Researchers Find Link Between Exercise and Sharper Thinking	Athletes Discuss Link Between Exercise and Sharper Thinking

Demographics. Finally, participants completed a demographics questionnaire assessing a range of background characteristics, including items on gender identity, age, ethnicity, and race. Participants also reported the state they live in, their education, line of work, religious affiliation, political party affiliation, and political ideology. Participants also indicated whether they were born in the U.S. and whether English is the first language they learned.

Procedure

Participants completed the experiment in a single online session lasting approximately 30 to 40 minutes via the Millisecond platform. After reviewing the experiment information and providing informed consent, participants completed the experimental components in the following order: (1) SC-IAT, (2) explicit science trust-suspicious scale, (3) explicit 4-dimensional trust in scientists measure, (4) PANAS, (5) scientific understanding measure, (6) BFI-10, (7) Science Process Skills Inventory, (8) NFC, (9) news article selection task, and (10) demographics questionnaire. Upon completing the experiment, I presented the participants with the debrief and provided information about the experiment's purpose and hypotheses.

Composites

In line with my pre-registered decision rule, I examined whether the explicit science trust-suspicious scale and the explicit 4-dimensional trust in scientists scale correlated at a threshold of $r > .70$ to combine them into a single composite. The two scales correlated at $r = .70$, therefore I created a single explicit trust composite by standardizing and averaging both measures. Higher composite scores reflect greater explicit trust in science and scientists.

I also examined the relationship between the Science Process Skills Inventory and the scientific understanding scale, but the correlation did not reach the pre-registered decision rule (r = .15), so I did not average them into a composite index.

Experiment 1 Pre-Registered Results

Predictive Validity of Implicit and Explicit Trust

I report descriptive statistics for the full and outlier-excluded sensitivity samples in Table 4, including implicit trust in science, all explicit trust measures (the explicit science trust-suspicious scale, the explicit 4-dimensional trust in scientists scale and its subscales of perceived competence, perceived integrity, perceived benevolence, and perceived openness, and the explicit trust composite), and science article selection. To test whether implicit trust in science and the explicit trust composite each contribute unique variance in predicting science article selection, I simultaneously regressed science article selection on both predictors. Because I tested three dependent variables, I applied a Bonferroni correction, setting the familywise alpha at α = .017 per dependent variable.

Table 4

Descriptive Statistics for Primary Dependent Variables

	Full Sample ($N = 96$)		Sensitivity Sample ($N = 93$)	
Measure	*M (SD)*	Range	*M (SD)*	Range
Implicit trust				
SC-IAT D-score	0.10 (0.32)	[-0.62, 1.16]	0.10 (0.30)	[-0.62, 0.91]
Explicit trust measures				
Science Trust-Suspicious Scale	5.94 (0.94)	[1.78, 7.00]	6.01 (0.77)	[3.33, 7.00]
4-Dimensional overall	4.11 (0.61)	[2.08, 5.00]	4.15 (0.56)	[2.58, 5.00]
Competence	4.48 (0.56)	[2.00, 5.00]	4.51 (0.49)	[3.00, 5.00]
Integrity	4.16 (0.74)	[1.67, 5.00]	4.21 (0.67)	[2.67, 5.00]
Benevolence	3.97 (0.76)	[1.67, 5.00]	4.01 (0.72)	[1.67, 5.00]
Openness	3.82 (0.84)	[1.00, 5.00]	3.85 (0.83)	[1.00, 5.00]
Explicit composite (z-avg)	0.02 (0.90)	[-3.74, 1.29]	0.00 (1.00)	[-3.32, 1.58]
Behavior				
Science article selection (prop.)	0.64 (0.24)	[0.20, 1.00]	0.63 (0.24)	[0.20, 1.00]

Note. Means and *SD*s are on original scales: Science Trust-Suspicious Scale (1-7), 4-Dimensional subscales (1-5), SC-IAT D-score (unbounded). Explicit composite is the z-scored average of the two explicit scales (range reflects z-score units). Subscale rows are from the 4-Dimensional Trust in Scientists scale.

The overall regression model was statistically significant, $F(2, 93) = 3.45$, $p = .036$, $R^2 = .069$, though it did not survive Bonferroni correction. The explicit trust composite significantly predicted science article selection, while implicit trust in science showed a marginal effect. Neither predictor survived the Bonferroni correction individually. Notably, the negative direction of the implicit trust in science effect indicates that participants with stronger implicit associations between science and trustworthiness selected fewer science articles (See Figure 1).

As pre-registered, I also ran sensitivity analyses excluding the three univariate outliers ($N = 93$), which yielded the same pattern but a stronger overall model that survived Bonferroni correction, $F(2, 90) = 5.00$, $p = .009$, $R^2 = .100$. Both predictors met the corrected significance threshold: implicit trust in science and the explicit trust composite. See full results in Table 5.

Table 5

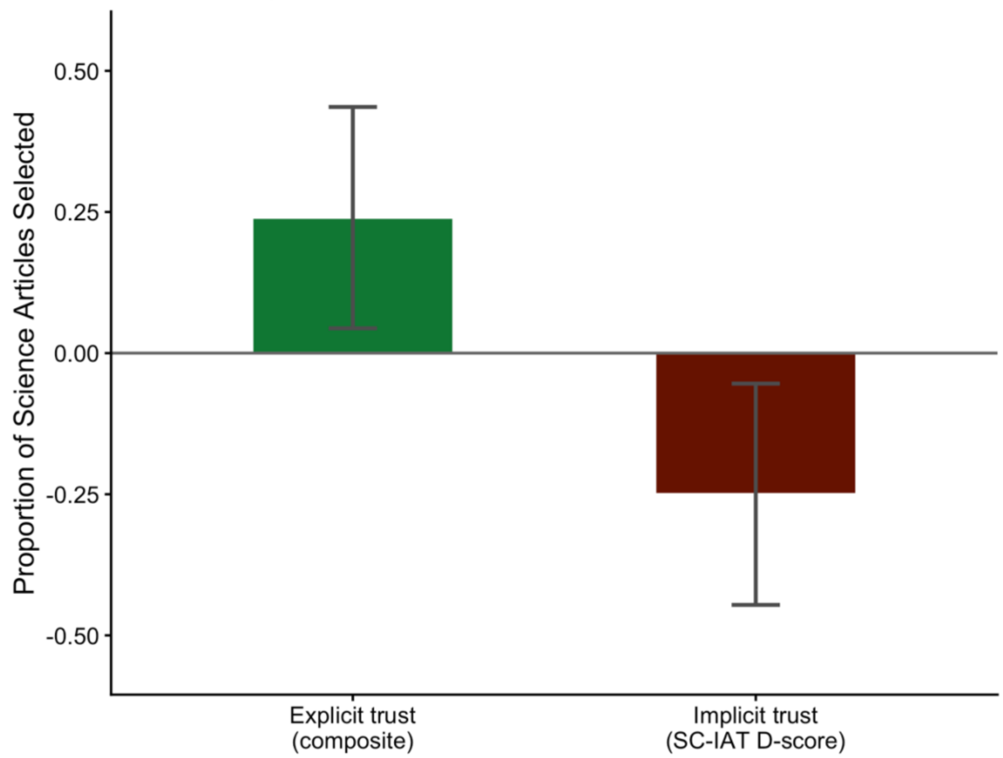
Multiple Regression Predicting Science Article Selection from Implicit and Explicit Trust Composite

	β (SE)	*t*	*p*
Full sample (N = 96)			
SC-IAT D-score	-.20 (.10)	-1.98	.051
Explicit trust composite	.25* (.11)	2.15	.034*
Sensitivity analysis (N = 93)			
SC-IAT D-score	-.25** (.10)	-2.44	.017**
Explicit trust composite	.24* (.10)	2.41	.018*

Note. β = standardized coefficient, *SE* = standard error. *$p < .05$, **p = significance level reached given Bonferroni correction.

Figure 1

Implicit and Explicit Trust in Science Predicting Science Article Selection



Although I created a composite from the explicit science trust-suspicious scale and the explicit 4-dimensional trust in scientists scale, each scale targets a conceptually distinct aspect of trust: trust in science as a body of knowledge versus trust in scientists as individuals. Therefore, I also ran exploratory regression models predicting science article selection from implicit trust in science and each explicit measure individually (e.g. behavior ~ SC-IAT D-score + explicit measure). These analyses were not Bonferroni-corrected. See results for each individual model presented in Table 6.

In the full sample ($N = 96$), the model including the explicit science trust-suspicious scale was statistically significant, with the explicit science trust-suspicious scale significantly predicting science article selection ($\beta = .23$, $p = .031$) and implicit trust in science showing a marginal negative effect ($\beta = -.20$, $p = .051$), consistent with the pattern observed using the explicit trust composite. The model including the explicit 4-dimensional trust in scientists scale overall score showed a marginal effect, with both the explicit 4-dimensional trust in scientists scale ($\beta = .18$, $p = .083$) and implicit trust in science ($\beta = -.19$, $p = .071$) showing marginal effects in the same direction. Among the subscales, perceived integrity showed a marginal positive effect on science article selection ($\beta = .20$, $p = .064$), as did perceived openness ($\beta = .18$, $p = .087$), with their respective models reaching marginal significance. Implicit trust in science showed a marginal negative effect in the perceived integrity ($\beta = -.20$, $p = .060$), perceived openness ($\beta = -.18$, $p = .088$), and perceived competence ($\beta = -.18$, $p = .093$) models. Perceived competence and perceived benevolence did not significantly predict science article selection (both ps $> .26$), and neither of those models reached significance (both ps $> .18$).

Sensitivity analyses excluding the three univariate outliers ($N = 93$) showed the same pattern but reached significance in more of the models. The model including the explicit science trust-suspicious scale was significant, with both the explicit science trust-suspicious scale ($\beta = .25$, $p = .015$) and implicit trust in science ($\beta = -.24$, $p = .018$) significantly predicting science article selection. The model including the explicit 4-dimensional trust in scientists scale overall score was significant, with implicit trust in science reaching significance ($\beta = -.24$, $p = .024$) and the explicit 4-dimensional trust in scientists scale showing a marginal positive effect ($\beta = .19$, $p = .067$). Among the subscales, the perceived integrity model was the strongest, surviving the Bonferroni threshold, with both perceived integrity ($\beta = .21$, $p = .040$) and implicit trust in science ($\beta = -.25$, $p = .018$) reaching significance. Perceived openness showed a marginal positive effect ($\beta = .17$, $p = .096$) with a significant overall model. The perceived competence model was marginal, with implicit trust in science significantly predicting science article selection ($\beta = -.23$, $p = .032$) but perceived competence not reaching significance ($p = .210$). The perceived benevolence model was marginal, with implicit trust in science significantly predicting science article selection ($\beta = -.21$, $p = .040$) but perceived benevolence not reaching significance ($p = .317$). Across both the full and sensitivity analysis samples, there was a clear pattern in the direction of effects: implicit trust in science negatively predicted science article selection and each explicit measure positively predicted science article selection, regardless of which explicit measure was used.

Table 6

Multiple Regression Predicting Science Article Selection from Implicit and Explicit Trust Individual and Sub-Scales

Explicit Measure	β_2 Explicit (*SE*)	β_1 IAT (*SE*)	Model *p*	Model R^2
Full sample ($N = 96$)				
Science Trust-Suspicious Scale	.23* (.10)	-.20† (.10)	.033*	.07
4-Dimensional overall	.18† (.10)	-.19† (.10)	.076†	.05
Explicit composite	.22* (.10)	-.20† (.10)	.036*	.07
Competence	.12 (.11)	-.18† (.11)	.184	.04
Integrity	.20† (.10)	-.20† (.10)	.061†	.06
Benevolence	.11 (.10)	-.16 (.10)	.199	.03
Openness	.18† (.10)	-.18† (.10)	.079†	.05
Sensitivity analysis ($N = 93$, outliers removed)				
Science Trust-Suspicious Scale	.25* (.10)	-.24* (.10)	.007*	.10
4-Dimensional overall	.19† (.10)	-.24* (.10)	.027*	.08
Explicit composite	.24* (.10)	-.25* (.10)	.009*	.10
Competence	.13 (.10)	-.23* (.10)	.065†	.05
Integrity	.21* (.10)	-.25* (.10)	.017*	.09
Benevolence	.10 (.10)	-.21* (.10)	.087†	.05
Openness	.17† (.10)	-.22* (.10)	.036*	.07

Note. Each row is a separate regression model: behavior ~ SC-IAT D-score + explicit measure. β_1 = SC-IAT D-score; β_2 = listed explicit measure. SE in parentheses. Model *p* = omnibus *F*-test significance. †$p < .10$. *$p < .05$.

Hierarchical Regression Analyses

To examine the unique contribution of each trust measure, I conducted hierarchical regression analyses. When I entered implicit trust in science first (Model 1), it did not significantly predict science article selection, $F(1, 94) = 2.19$, $p = .142$, R^2 =

.023. Adding the explicit trust composite in Model 2 resulted in a significant improvement in model fit, $F(1, 93) = 3.45$, $p = .036$, $R^2 = .069$, with the change reaching significance, $\Delta R^2 = .046$, $F(1, 93) = 4.62$, $p = .034$, indicating that the explicit trust composite accounted for meaningful additional variance beyond implicit trust in science. When I entered the explicit trust composite first (Model 3), it showed a marginal effect on science article selection, $F(1, 94) = 2.89$, $p = .092$, $R^2 = .030$. Adding implicit trust in science in Model 4 produced a significant overall model, $F(1, 93) = 3.45$, $p = .036$, $R^2 = .069$, though the unique contribution of implicit trust in science was marginal, $\Delta R^2 = .039$, $F(1, 93) = 3.91$, $p = .051$, suggesting a pattern whereby implicit trust in science accounted for additional variance beyond the explicit trust composite.

I also ran sensitivity analyses excluding the three univariate outliers ($N = 93$). When I entered implicit trust in science first (Model 1), it significantly predicted science article selection, $F(1, 91) = 4.01$, $p = .048$, $R^2 = .042$. Adding the explicit trust composite in Model 2 resulted in a significant improvement in model fit, $F(1, 90) = 5.00$, $p = .009$, $R^2 = .100$, with the change reaching significance, $\Delta R^2 = .058$, $F(1, 90) = 5.78$, $p = .018$, indicating that the explicit trust composite accounted for meaningful additional variance beyond implicit trust in science. When I entered the explicit trust composite first (Model 3), it showed a marginal effect on science article selection, $F(1, 91) = 3.86$, $p = .052$, $R^2 = .041$. Adding implicit trust in science in Model 4 resulted in a significant improvement in model fit, $F(1, 90) = 5.00$, $p = .009$, $R^2 = .100$, with the change reaching significance, $\Delta R^2 = .059$, $F(1, 90) = 5.94$, $p = .017$, indicating that implicit trust in science accounted for meaningful additional variance beyond the explicit trust composite. There was a consistent pattern in the direction and magnitude across the full and outlier-excluded samples. See full results in Table 7.

Table 7

Hierarchical Regression Analyses Predicting Science Article Selection

	β (SE)	R^2	ΔR^2
Full sample (N = 96)			
Model 1: Implicit only		.023	
SC-IAT D-score	-.15 (.10)		
Model 2: + Explicit trust		.069	.046*
SC-IAT D-score	-.20† (.10)		
Explicit trust composite	.22* (.10)		
Model 3: Explicit trust only		.030	
Explicit trust composite	.17† (.10)		
Model 4: + Implicit trust		.069	.039†
Explicit trust composite	.22* (.10)		
SC-IAT D-score	-.20† (.10)		
Sensitivity analysis: Outliers removed (N = 93)			
Model 1: Implicit only		.042	
SC-IAT D-score	-.21* (.10)		
Model 2: + Explicit trust		.100	.058*
SC-IAT D-score	-.25* (.10)		
Explicit trust composite	.24* (.10)		
Model 3: Explicit trust only		.041	
Explicit trust composite	.20† (.10)		
Model 4: + Implicit trust		.100	.059*
Explicit trust composite	.24* (.10)		
SC-IAT D-score	-.25* (.10)		

Note. β values are standardized coefficients. ΔR^2 reflects the change in R^2 when adding the second predictor. *$p < .05$, †$p < .10$.

Experiment 1 Discussion

Experiment 1 provided evidence that implicit and explicit trust in science each contribute unique variance in predicting science article selection. The finding that each measure explained roughly equal unique variance ($\Delta R^2 \approx .06$ in each direction) is consistent with dual-process theories of attitudes and behavior (Chaiken & Trope, 1999; Gawronski & Bodenhausen, 2006) and extends prior work by Schoor and Schütz (2021) to a behavioral outcome domain.

Interestingly, I found that implicit trust in science had a negative relationship with science article selection; participants with stronger implicit associations between science and trustworthiness selected fewer science articles. This pattern held consistently across nearly all explicit measures examined in the exploratory analyses. One possibility is that automatic positive associations with science do not translate straightforwardly into deliberate engagement with science content. Another possibility is that implicit trust in science may reflect a kind of complacency in a sense, such that science is trustworthy without needing to actively seek it out. Alternatively, the SC-IAT may be capturing a somewhat different construct than intended in this context, and the divergence between implicit and explicit trust may itself be theoretically informative. I return to these possibilities in the general discussion.

Another important thing to note is that in all of my analyses, the sensitivity sample that excluded three univariate outliers yielded a stronger and more interpretable pattern than in the full sample. In the full sample, neither predictor individually survived Bonferroni correction; in the sensitivity sample, both did. This pattern held across both the regression analyses and the exploratory subscale models. The three excluded participants were identified as univariate outliers based on a standard criterion of more than 3 SDs from the mean on at least one primary dependent variable, and their removal did not change the direction of any effect, only the precision of the estimates. This suggests the full-sample results are not misleading, but rather somewhat attenuated by the presence of extreme values.

Overall, Experiment 1 established the foundational concept of implicit and explicit trust in science, supporting the idea that each contributes unique variance to a science-related behavior. Experiment 2 extends these findings by examining how trust in science and behavior might be affected under different conditions. Specifically, Experiment 2 explores whether the framing of science communication influences implicit trust in science, the explicit trust composite, and science article selection.

Experiment 2

While Experiment 1 assessed the relative predictive validity of implicit and explicit trust in science by treating them as predictors of behavior, Experiment 2 shifts these measures from predictors to outcome variables. By shifting the implicit and explicit variables to outcomes, I can investigate how science framing and individual-level scientific knowledge actively shape trust in science and trust in science-related behavior.

Experiment 2 introduces a between-subjects manipulation of science framing, presenting science as either static and unchanging or dynamic and evolving, to test whether framing influences trust. The framing manipulation is informed by research on norm-based framing, which suggests that emphasizing change over time (dynamic norms) can be more effective than emphasizing stability or tradition (static norms) when shaping attitudes and motivating behavior (Ma & Reynolds-Tylus, 2024; Sparkman & Walton, 2017). Within the context of science communication, framing science as dynamic may foster greater trust among people who understand science as an evolving process. However, for people with lower scientific knowledge, dynamic framing may introduce perceived ambiguity, potentially undermining trust in science.

To examine these individual differences, Experiment 2 incorporates the measures of scientific knowledge to test whether participants' understanding of science moderates the effect of framing on trust. Prior work suggests people with higher scientific knowledge are better equipped to interpret evolving evidence and resist misinformation (Čavojová et al., 2023; Slater et al., 2019). Thus, I hypothesized that participants with higher scientific knowledge would show greater trust in science (implicitly and explicitly) when exposed to dynamic framing, whereas people with lower scientific knowledge would show greater trust under static framing. By manipulating framing and measuring both implicit and explicit trust, Experiment 2 aims to better understand how communication strategies interact with individual knowledge to shape public trust in science and science-related behavior.

Methods

Participants

I conducted an a priori power analysis using G*Power to determine the minimum required sample size for an independent-samples t-test comparing two framing conditions (static vs. dynamic science). Using a small to medium effect size (d = 0.35), a significance level of $\alpha = .05$, and a desired power of 0.80, the analysis indicated that a total sample size of 204 participants (102 per group) would be required to detect a statistically significant difference between conditions using a one-tailed test. In addition, I ran a power analysis to determine the minimum required sample size for a linear multiple regression with 3 predictors (scientific framing, scientific knowledge, and the interaction term between them). Using a medium effect size ($f^2 = .15$), significance level of $\alpha = .05$, and a desired power of 0.80, the analysis indicated that a total sample size of 43 participants would be required to detect a statistically significant effect of the predictors.

I collected data from a total of 210 participants. I excluded participants if they: (a) failed the embedded attention check item ($n = 19$), (b) met SC-IAT exclusion criteria (fewer than 50% correct or more than 10% of trials with reaction times under 300 ms; $n = 7$); or (c) had missing data on a primary dependent variable ($n = 3$). I additionally excluded 12 participants who completed portions of the experiment more than once, as these individuals may have been exposed to the manipulation twice due to technical errors. The final sample consisted of $N = 171$ participants (80 men, 90 women) recruited via CloudResearch Connect. The mean age was 44.51 years ($SD = 16.19$, range 20-82). The majority identified as non-Hispanic or Latino/a (82.5%). Approximately 43% identified as Democrat and 19% as Republican. About half identified as Christian (49.1%), and 44% identified as non-religious (atheist, agnostic, or no religion). After exclusions, I had an even distribution of participants across the static framing ($n = 85$) and dynamic framing ($n = 86$) conditions. Full sample characteristics are presented in

Table 8. I identified four additional participants as univariate outliers (more than 3 *SD*s from the mean on at least one primary dependent variable) and excluded from sensitivity analyses ($N = 167$).

Table 8
Experiment 2 Sample Characteristics

	Characteristic	*n*	%
Gender	Man	80	46.8%
	Woman	90	52.6%
Ethnicity	Hispanic or Latino/a	28	16.4%
	Not Hispanic or Latino/a	141	82.5%
	Unknown/prefer not to say	1	0.6%
Education	Less than high school	1	0.6%
	High school diploma	23	13.5%
	Associate's degree	16	9.4%
	Some college	38	22.2%
	Bachelor's degree	68	39.8%
	Master's degree	17	9.9%
	Doctorate degree	2	1.2%
	Professional degree	5	2.9%
Political party	Democratic Party	74	43.3%
	Republican Party	32	18.7%
	Independent	44	25.7%
	Libertarian Party	3	1.8%
	Green Party	1	0.6%
	No party affiliation	12	7.0%
	Other	3	1.8%
Political views	Very liberal	30	17.5%
	Liberal	31	18.1%
	Slightly liberal	21	12.3%
	Moderate	36	21.1%
	Slightly conservative	17	9.9%
	Conservative	22	12.9%
	Very conservative	8	4.7%
	Do not identify	5	2.9%
Religion	Christian	84	49.1%
	Agnostic	41	24.0%
	Atheist	18	10.5%
	No religion	17	9.9%
	Buddhist	3	1.8%
	Muslim	3	1.8%
	Jewish	1	0.6%
	Not listed / other	3	1.8%
Continuous variables	Age	M = 44.51, SD = 16.19, range 20-82	
	Political interest (1-7)	M = 5.24, SD = 1.63	

Note. N = 171

Design

For Experiment 2, I used a between-subjects experimental design with one manipulated factor: science framing (static vs. dynamic). I randomly assigned participants to one of two framing conditions and then they completed the outcome measures assessing trust in science and behavior. The primary dependent variables include implicit trust in science, explicit trust in science, and the news article selection task. I also measured scientific knowledge as a moderator.

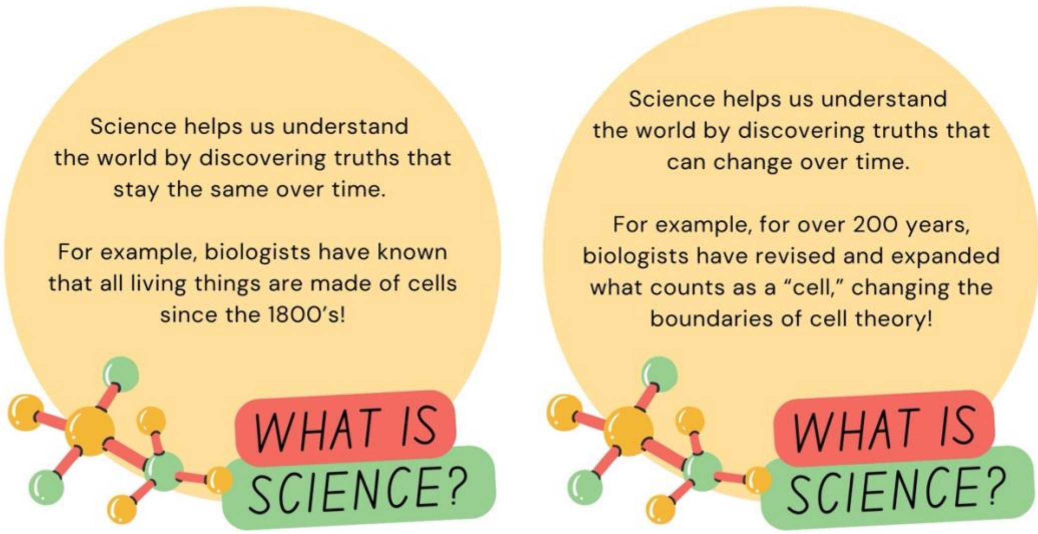
Materials

Participants completed the same SC-IAT for the implicit measure, explicit measures, scientific knowledge measures, filler task, news article selection task, and demographics items as in Experiment 1. In addition, I randomly assigned participants to one of two science framing conditions. The static framing condition presented science as unchanging and absolute. The dynamic framing condition presented science as evolving and subject to new discoveries.

Static versus Dynamic Framing of Science. Participants randomly received one of two science presentations: a static framing condition or a dynamic framing condition. For the static framing, participants saw an infographic that stated, “Science helps us understand the world by finding truths that stay the same over time. For example, biologists have known that all living things are made of cells since the 1800’s!”. For the dynamic framing condition, participants saw an infographic that stated, “Science helps us understand the world by discovering truths that can change over time. For example, for over 200 years, biologists have revised and expanded what counts as a ‘cell,’ changing the boundaries of cell theory!" I presented the information as an infographic labeled, "What is science?" in the corner on a green and red background with a molecule next to it, and the static or dynamic information presented on a yellow background (see Figure 2). I pretested multiple static and dynamic examples in a CloudConnect participant sample (see Supplemental Materials). In the pretest, I had participants rate all examples asking, "After reading this, how effectively do you think this graphic teaches the lesson that scientific knowledge is UPDATED/CONSISTENT?" in addition to how believable the information was. I chose the matching category examples that had the highest ratings on believability and as science being seen as updated or consistent for dynamic and static, respectively. Following the presentation of the science framing information, I asked participants to rate their agreement with the statements, "I agree with the way science is described in the message" and "I found the message about science to be clear and understandable," using a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

Figure 2

Static and Dynamic Framing of Science



Procedure

Participants completed the experiment in a single online session lasting approximately 30 to 40 minutes via the Millisecond platform. After reviewing the experiment information and providing informed consent, participants completed the experimental components in the following order: (1) scientific framing manipulation, (2) framing follow-up questions, (3) SC-IAT, (4) explicit science trust-suspicious scale, (5) explicit 4-dimensional trust in scientists measure, (6) PANAS, (7) scientific knowledge measure, (8) BFI-10, (9) Science Process Skills Inventory, (10) NFC, (11) news article selection task, and (12) demographics questionnaire. Upon completing the experiment, I presented the participants with the debrief and provided information about the experiment's purpose and hypotheses.

Composites

In line with my pre-registered decision rule, I examined whether the explicit science trust-suspicious scale and the explicit 4-dimensional trust in scientists scale correlated at a threshold of $r > .70$ to combine them into a single composite. The two scales correlated at $r = .75$, therefore I created a single explicit trust composite by standardizing and averaging both measures. Higher composite scores reflect greater explicit trust in science and scientists.

I also examined the relationship between the Science Process Skills Inventory and the scientific understanding scale, but the correlation did not reach the pre-registered decision rule ($r = .19$), so I did not average them into a composite index.

Analytic Approach

I report descriptive statistics for implicit trust in science, all explicit trust measures (the explicit science trust-suspicious scale, the explicit 4-dimensional trust in scientists scale and its subscales of perceived competence, perceived integrity, perceived benevolence, and perceived openness, and the explicit trust composite), and science article selection by condition in Table 9. Although I had directional hypotheses for Experiment 2, I treat these analyses as exploratory given that the present work is one of the first investigations of static versus dynamic science communication framing on implicit trust in science, the explicit trust composite, and science article selection simultaneously. Therefore, I conducted all *t*-tests and regression analyses as two-tailed tests. I applied the Bonfecrroni correction across the three primary dependent variables (α = .017). Importantly, prior to data collection I powered the study to detect a medium effect size using G*Power. However, due to a higher-than-anticipated number of exclusions, the final analyses are slightly underpowered. Following the wise words of

Bob Rosenthal, I interpret patterns of results and effect sizes alongside significance values throughout.

Table 9

Descriptive Statistics for Primary Variables and Subscales by Framing Condition

Measure	Static *M* (*SD*)	Dynamic *M* (*SD*)
Dependent variables		
SC-IAT D-score	0.09 (0.32)	0.16 (0.33)
Explicit trust composite	-0.18 (1.00)	0.18 (0.84)
Science Trust-Suspicious Scale	5.99 (0.58)	6.19 (0.52)
4-Dimensional overall	3.99 (0.65)	4.28 (0.62)
Competence	4.42 (0.57)	4.64 (0.57)
Integrity	4.07 (0.71)	4.28 (0.72)
Benevolence	3.84 (0.79)	4.14 (0.78)
Openness	3.64 (0.82)	4.06 (0.87)
Science article selection (prop.)	0.60 (0.25)	0.61 (0.26)
Manipulation check items		
Message clarity	4.61 (0.58)	4.38 (0.77)
Message agreement	4.45 (0.72)	4.26 (0.84)

Note. Means and *SD*s are on original scales: Science Trust-Suspicious Scale (1-7), 4-Dimensional subscales (1-5), SC-IAT D-score (unbounded). Explicit composite is the z-scored average of the two explicit scales (range reflects z-score units). Subscale rows are from the 4-Dimensional Trust in Scientists scale.

Experiment 2 Pre-Registered Results

Manipulation Check

Participants in the static framing condition rated the science message as significantly more clear ($M = 4.61$, $SD = 0.58$) than those in the dynamic condition ($M = 4.38$, $SD = 0.77$), $t(157.89) = 2.19$, $p = .030$, $d = 0.33$. The two conditions did not differ in their agreement with the science description (static: $M = 4.45$, $SD = 0.72$; dynamic: $M = 4.26$, $SD = 0.84$), $t(165.25) = 1.60$, $p = .111$, $d = 0.24$. The manipulation produced a clarity difference but did not result in differential agreement with the framing content.

Effects of Science Framing on Implicit Trust, Explicit Trust, and Behavior

I examined whether static versus dynamic framing differed on implicit trust in science, the explicit trust composite, and science article selection using independent-samples *t*-tests. Science framing did not significantly affect implicit trust in science, though descriptively, the dynamic condition showed higher implicit trust in science than the static condition (see Figure 3). Science framing significantly affected the explicit trust composite such that the dynamic condition showed higher explicit trust than the static condition (see Figure 4). Science framing did not significantly affect science article selection. Sensitivity analyses excluding outliers ($N = 167$) yielded the same pattern for all three primary dependent variables. See full results in Table 10.

Figure 3

Static and Dynamic Framing Differences in Implicit Trust in Science

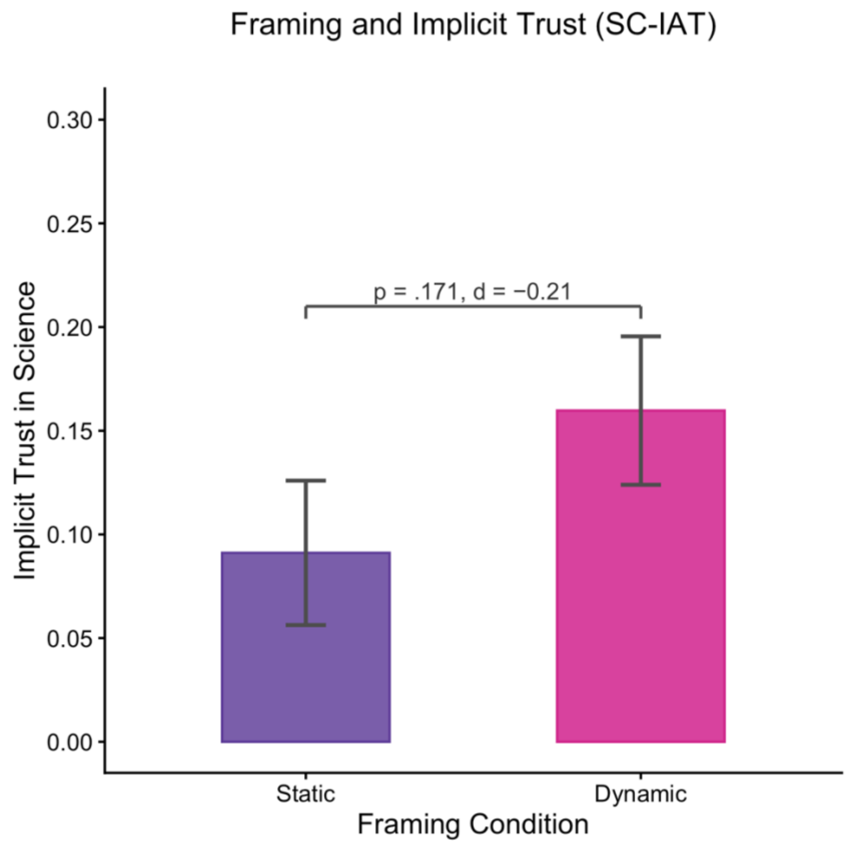
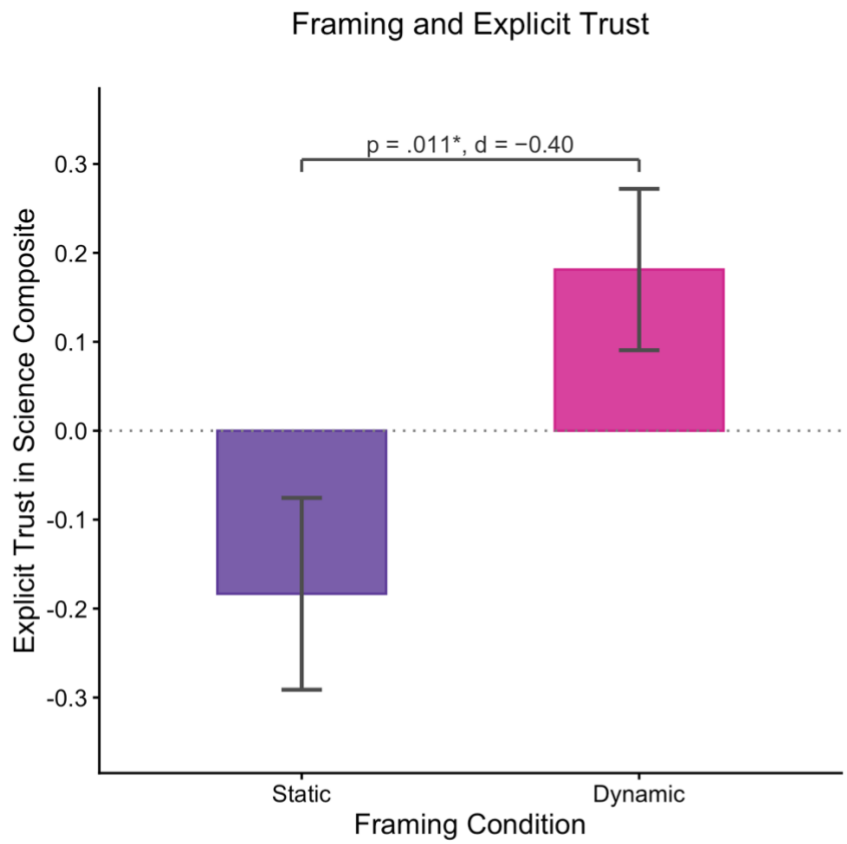


Figure 4

Static and Dynamic Framing Differences in Explicit Trust in Science Composite



Explicit Trust Subscales

To further investigate the explicit trust effect, I also examined the explicit science trust-suspicious scale and the four subscales of the explicit 4-dimensional trust in scientists scale separately. The explicit science trust-suspicious scale showed a marginal effect in the same direction as the composite such that the dynamic condition showed higher scores than the static condition. The explicit 4-dimensional trust in scientists scale overall score showed a significant effect, with the dynamic condition showing higher trust in scientists than the static condition. Among the subscales, dynamic framing produced significantly higher perceived openness, perceived competence, and perceived benevolence; perceived integrity showed a marginal effect in the same direction (see Figure 5). See full results in Table 10.

Table 10

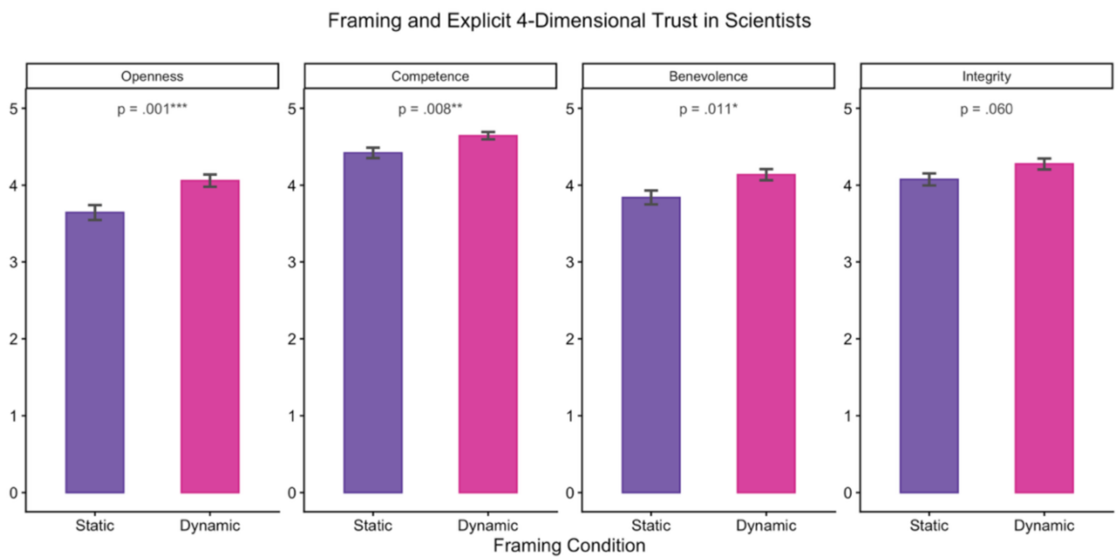
Two-Tailed Independent-Samples T-Tests: Effect of Science Framing on Trust and Behavior

Measure	Static *M (SD)*	Dynamic *M (SD)*	*t*	*p*	*d*
Primary dependent variables					
SC-IAT D-score	0.09 (0.32)	0.16 (0.33)	-1.37	.171	0.21
Explicit trust composite	-0.18 (1.00)	0.18 (0.84)	-2.59	.011*	0.40
Science article selection	0.60 (0.25)	0.61 (0.26)	-0.24	.813	0.04
Exploratory subscales					
Science Trust-Suspicious Scale	5.99 (0.81)	6.19 (0.70)	-1.76	.080	0.27
4-Dimensional overall	3.99 (0.66)	4.28 (0.53)	-3.09	.002**	0.48
Competence	4.42 (0.62)	4.64 (0.45)	-2.70	.008**	0.42
Integrity	4.07 (0.72)	4.28 (0.66)	-1.89	.060	0.29
Benevolence	3.84 (0.83)	4.14 (0.67)	-2.57	.011*	0.40
Openness	3.64 (0.90)	4.06 (0.74)	-3.30	.001**	0.51

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

Figure 5

Static and Dynamic Framing Differences in 4-Dimensional Subscales



Moderated Regression: Scientific Knowledge as Moderator

I tested whether scientific knowledge moderated the effect of framing on each primary dependent variable using two sets of moderated regression models: one using the objective scientific knowledge accuracy score as the moderator and one using the Science Process Skills Inventory sum score as the moderator. Each model included framing, the knowledge measure, and their interaction term. See full results in Tables 11 and 12.

Using objective scientific knowledge accuracy as the moderator, no significant main effects of framing or knowledge emerged for any of the three primary dependent variables, and no framing × knowledge interactions were significant (all *p*s > .59). Exploratory models using the explicit 4-dimensional trust in scientists subscales as outcomes similarly showed no significant interactions, though the overall model fit was significant for the 4-dimensional overall score, $F(3, 167) = 3.63$, $p = .014$, and the perceived openness subscale, $F(3, 167) = 4.40$, $p = .005$, without any individual predictor reaching significance.

The Science Process Skills Inventory significantly and positively predicted implicit trust in science as a main effect ($b = 0.01$, $SE = 0.01$, $t = 2.06$, $p = .041$), indicating that participants with stronger self-reported science process skills showed stronger implicit associations between science and trustworthiness, independent of framing condition. No framing × Science Process Skills Inventory interactions were significant for any dependent variable. In exploratory subscale models, the Science Process Skills Inventory showed a marginal positive main effect on perceived openness ($b = 0.02$, $p = .065$), suggesting that stronger science process skills may also be associated with perceiving scientists as more open to feedback. The overall model fit for the explicit trust composite was significant when using the Science Process Skills Inventory, $F(3, 167) = 2.78$, $p = .043$, though no individual predictor reached significance. I did not calculate any simple slopes as no interactions reached significance in either model set.

Table 11

Moderated Regression Using Objective Scientific Knowledge Accuracy as Moderator

Predictor	*b*	*t*	*p*
Model A: SC-IAT D-score			
Framing	0.03 (0.13)	0.25	.805
Scientific knowledge	0.00 (0.02)	0.02	.980
Framing × Acc.	0.01 (0.03)	0.29	.774
Model B: Explicit trust composite			
Framing	0.36 (0.37)	0.95	.342
Scientific knowledge	0.02 (0.05)	0.38	.703
Framing × Acc.	0.00 (0.07)	0.02	.988
Model C: Science article selection			
Framing	-0.04 (0.10)	-0.42	.678
Scientific knowledge	0.00 (0.02)	0.21	.837
Framing × Acc.	0.01 (0.02)	0.53	.597
Exploratory subscale models (outcome = 4-Dim subscale)			
4-Dimensional overall			
Framing	0.25 (0.24)	1.01	.312
Scientific knowledge	0.02 (0.04)	0.68	.496
Framing × Acc.	0.01 (0.05)	0.15	.883
Openness			
Framing	0.24 (0.33)	0.74	.463
Scientific knowledge	0.03 (0.05)	0.56	.576
Framing × Acc.	0.04 (0.07)	0.54	.593

Note. Framing was dummy-coded (0 = static, 1 = dynamic). Scientific knowledge = raw score on 9-item science quiz. Only models that reached significance are shown for subscale models. **p* < .05. †*p* < .10.

Table 12

Moderated Regression Using Science Process Skills Inventory as Moderator

Predictor	*b*	*t*	*p*
Model A: SC-IAT D-score			
Framing	0.28 (0.22)	1.24	.216
SPSI sum	0.01 (0.01)	2.06	.041*
Framing × SPSI	-0.01 (0.01)	-0.97	.333
Model B: Explicit trust composite			
Framing	0.26 (0.64)	0.41	.685
SPSI sum	0.01 (0.01)	0.75	.456
Framing × SPSI	0.00 (0.02)	0.16	.870
Model C: Science article selection			
Framing	-0.05 (0.18)	-0.30	.765
SPSI sum	0.00 (0.00)	0.59	.556
Framing × SPSI	0.00 (0.01)	0.35	.724
Exploratory subscale models (outcome = 4-Dim subscale)			
4-Dimensional overall			
Framing	0.26 (0.42)	0.62	.539
SPSI sum	0.01 (0.01)	0.62	.538
Framing × SPSI	0.00 (0.01)	0.06	.950
Openness			
Framing	0.70 (0.56)	1.25	.213
SPSI sum	0.02 (0.01)	1.86	.065†
Framing × SPSI	-0.01 (0.02)	-0.54	.591

Note. Framing was dummy-coded (0 = static, 1 = dynamic). SPSI = Science Process Skills Inventory sum score (range 11 - 44; higher = stronger self-reported science process skills). Only models that reached significance are shown for subscale models. *$p < .05$. †$p < .10$.

Experiment 2 Discussion

Experiment 2 produced a mixed pattern of results. Dynamic framing was associated with numerically (but not significantly) higher implicit trust in science and significantly higher explicit trust compared to static framing. Exploratory subscale analyses revealed that dynamic framing particularly enhanced perceptions of scientists' perceived openness, perceived competence, and perceived benevolence. Contrary to my hypotheses, objective scientific knowledge accuracy did not moderate framing effects on any dependent variable. However, the science process skills independently predicted higher implicit trust in science regardless of framing condition, suggesting that science process skills may be a meaningful individual difference in trust formation. Science framing did not significantly affect science article selection in either the full or sensitivity samples.

Experiment 3 extends these findings by crossing the static versus dynamic framing manipulation with a scientific uncertainty manipulation, examining whether the framing effect on implicit and explicit trust in science replicates and whether uncertainty interacts with framing to affect trust and behavior.

Experiment 3

In Experiment 2, I tested how science framing interacts with scientific knowledge to affect implicit and explicit trust in science and behavior. Experiment 3 expands on Experiment 2 by introducing uncertainty and specifically, how uncertainty and framing jointly shape trust and behavior, and whether these effects vary based on people's scientific knowledge. Uncertainty is an inherent part of science, but the way it is communicated can reduce trust, especially when audiences lack a strong understanding of the scientific process (Kreps & Kriner, 2020; van der Bles et al., 2020). By manipulating both uncertainty and framing, Experiment 3 tests whether scientific knowledge buffers against the negative effects of uncertainty, particularly under dynamic framing, which emphasizes change and may heighten perceptions of ambiguity. The goal of this experiment is to further understand how contextual factors of science communication (uncertainty) and communication strategies (framing) interact with individual scientific knowledge to shape implicit and explicit trust in science, as well as science-related behavioral choices.

Methods

Participants

I conducted an a priori power analysis using G*Power to determine the minimum required sample size for a 2 (uncertainty: low vs. high) × 2 (science framing: static vs. dynamic) between-subjects ANOVA. Assuming a medium effect size ($f = 0.25$), a significance level of $\alpha = .05$, and a desired power of 0.80, the analysis indicated that a minimum of 269 participants would be required to detect significant main effects or interactions across the four experimental conditions. In addition, I ran a power analysis to determine the minimum required sample size for a linear multiple regression with 7 predictors: three main effects (framing, uncertainty, and science process skills), three two-way interactions (framing × uncertainty, framing × science process skills, and uncertainty × science process skills), and one three-way interaction (framing × uncertainty × science process skills). Using a medium effect size ($f^2 = .15$), significance level of $\alpha = .05$, and a desired power of 0.80, the analysis indicated that a total sample size of 43 participants would be required to detect a statistically significant effect of the predictors.

I collected data from a total of 293 participants. I excluded participants if they: (a) failed the embedded attention check item ($n = 29$), (b) met SC-IAT exclusion criteria (fewer than 50% correct or more than 10% of trials with reaction times under 300 ms; $n = 8$); or (c) had missing data on a primary dependent variable ($n = 7$). I additionally excluded 19 participants who completed portions of the experiment more than once, as these individuals may have been exposed to the manipulation twice due to technical errors. The final sample consisted of $N = 228$ participants (105 men, 117 women, 6 other/prefer not to answer) recruited via CloudResearch Connect. The mean age was 45.68 years ($SD = 16.90$, range 19-82). The majority identified as non-Hispanic or Latino/a (84.6%). Approximately 46% identified as Democrat and 24% as Republican. About half identified as Christian (47.8%), and approximately 46% were non-religious. After exclusions, I still had a relatively balanced number of participants distributed across four conditions: static/low uncertainty ($n = 59$), static/high uncertainty ($n = 48$), dynamic/low uncertainty ($n = 60$), and dynamic/high uncertainty ($n = 61$). Full sample characteristics are presented in Table 13. I identified three additional participants as univariate outliers (more than 3 *SD*s from the mean on at least one primary dependent variable) and excluded from sensitivity analyses ($N = 225$).

Table 13
Experiment 3 Sample Characteristics

	Characteristic	*n*	%
Gender	Man	105	46.1%
	Woman	117	51.3%
	Trans-Man	3	1.3%
	Non-Binary	1	0.4%
Ethnicity	Hispanic or Latino/a	34	14.9%
	Not Hispanic or Latino/a	193	84.6%
Education	High school diploma	25	11.0%
	Associate's degree	35	15.4%
	Some college	46	20.2%
	Bachelor's degree	81	35.5%
	Master's degree	30	13.2%
	Doctorate degree	4	1.8%
	Professional degree	5	2.2%
Political party	Democratic Party	105	46.1%
	Republican Party	54	23.7%
	Independent	51	22.4%
	Libertarian Party	2	0.9%
	No party affiliation	13	5.7%
	Prefer not to answer	3	1.3%
Political views	Very liberal	37	16.2%
	Liberal	59	25.9%
	Slightly liberal	28	12.3%
	Moderate	37	16.2%
	Slightly conservative	17	7.5%
	Conservative	31	13.6%
	Very conservative	12	5.3%
	Do not identify / prefer not	7	3.1%
Religion	Christian	109	47.8%
	Agnostic	46	20.2%
	Atheist	32	14.0%
	No religion	27	11.8%
	Muslim	3	1.3%
	Buddhist	2	0.9%
	Hindu	1	0.4%
	Jewish	1	0.4%
	Not listed / prefer not	7	3.1%
Continuous variables	Age	M = 45.68, SD = 16.90, range 19-82	
	Political interest (1-7)	M = 5.36, SD = 1.51	

Note. N = 228

Design

For Experiment 3, I implemented a 2 (uncertainty condition: high vs. low) × 2 (science framing: static vs. dynamic) between-subjects design. I randomly assigned participants to one of the four experimental conditions and then they completed the outcome measures assessing trust in science and behavior. The primary dependent variables include implicit trust in science, explicit trust in science, and a news article selection task. In addition, I measured scientific knowledge to include as a moderator.

Materials

Participants completed the same static and dynamic framing conditions, SC-IAT for the implicit measure, explicit measures, scientific knowledge measures, filler tasks, news article selection task, and demographics items as in Experiments 1 and 2. In addition, Experiment 3 introduced an uncertainty task to manipulate participants' experiences of uncertainty.

Uncertainty Task. I randomly assigned participants to read one of two vignettes that varied in the extent to which scientific researchers agree about how to respond to a regional health risk (see Figure 6). The high-uncertainty condition states that scientific researchers disagree (act/wait). The low-uncertainty condition states that scientific researchers agree (act/act). After 10 seconds passed, an "ACT" and "WAIT" button appeared on screen. After reading the vignette, participants decided by clicking "ACT" or "WAIT". I chose to require participants to make an active choice because it engages participants directly with the uncertainty manipulation, rather than positioning them as passive observers. Following their decision, participants completed two follow-up items assessing their subjective experience of uncertainty: (1) “How confident are you in this decision?” and (2) “To what extent did you feel uncertain about the decision you were asked to make?” Both items are rated on a 7-point Likert scale (1 = Not at all, 7 = Extremely).

Figure 6

High and Low Uncertainty Task Vignettes

A previously undetected chemical compound has been found in soil samples from several neighborhoods in your region. Scientists are divided on the potential health effects from exposure.

Some scientific researchers have reviewed existing data on this issue and recommend immediate action should be taken. Other scientific researchers have begun collecting new data on this specific situation and recommend waiting until their data collection is complete before taking action.

You are asked to weigh in on this situation. What decision should be made?

A previously undetected chemical compound has been found in soil samples from several neighborhoods in your region. Scientists are aligned on the potential health effects from exposure.

Some scientific researchers have reviewed existing data on this issue and recommend immediate action should be taken. Other scientific researchers have begun collecting new data on this specific situation and also recommend immediate action should be taken.

You are asked to weigh in on this situation. What decision should be made?

Note. “ACT” and “WAIT” buttons appeared on screen after 10 seconds.

Procedure

Participants completed the experiment in a single online session lasting approximately 30 to 40 minutes via the Millisecond platform. After reviewing the experiment information and providing informed consent, participants completed the experimental components in the following order: (1) scientific framing manipulation, (2) framing follow-up questions, (3) scientific uncertainty manipulation, (4) scientific uncertainty follow-up questions, (5) SC-IAT, (6) explicit science trust-suspicious scale, (7) explicit 4-dimensional trust in scientists measure, (8) PANAS, (9) scientific understanding measure, (10) BFI-10, (11) Science Process Skills Inventory, (12) NFC, (13) news article selection task, and (14) demographics questionnaire. Upon completing the experiment, I presented the participants with the debrief and provided information about the experiment's purpose and hypotheses.

Composites

In line with my pre-registered decision rule, I examined whether the explicit science trust-suspicious scale and the explicit 4-dimensional trust in scientists scale correlated at a threshold of $r > .70$ to combine them into a single composite. The two scales correlated at $r = .75$; therefore, I created a single explicit trust composite by standardizing and averaging both measures. Higher composite scores reflect greater explicit trust in science and scientists. I also examined the relationship between the Science Process Skills Inventory and the scientific understanding scale, but the correlation did not reach the pre-registered decision rule ($r = .07$), so I did not average them into a composite index.

Analytic Approach

I report descriptive statistics for implicit trust in science, all explicit trust measures (the explicit science trust-suspicious scale, the explicit 4-dimensional trust in scientists scale and its subscales of perceived competence, perceived integrity, perceived benevolence, and perceived openness, and the explicit trust composite), and science article selection by condition in Table 14. Consistent with Experiment 2, I conducted all analyses as two-tailed tests and applied the Bonferroni correction across the three primary dependent variables ($\alpha = .017$). I conducted two-way ANOVAs (framing × uncertainty) for each dependent variable, with significant interactions followed up using Tukey's HSD. I ran three-way moderated regression analyses to test whether scientific knowledge moderated the framing × uncertainty interaction, using both objective scientific knowledge accuracy and the Science Process Skills Inventory as separate moderators. I also ran simple slopes at +1 *SD* and -1 *SD* of the Science Process Skills Inventory for any significant or marginal interactions. Similar to Experiment 2, due to a higher-than-anticipated number of exclusions, the final analyses are slightly underpowered, but I interpret patterns of results and effect sizes alongside significance values throughout.

Table 14

Descriptive Statistics for All Measures by Condition

Measure	Static/Low *M* (*SD*)	Static/High *M* (*SD*)	Dynamic/Low *M* (*SD*)	Dynamic/High *M* (*SD*)
Dependent variables				
SC-IAT D-score	0.11 (0.30)	0.14 (0.35)	0.31 (0.30)	0.22 (0.31)
Explicit trust composite	0.03 (1.00)	-0.11 (0.99)	0.09 (0.82)	-0.03 (0.95)
Science Trust-Suspicious Scale	6.10 (0.88)	5.88 (0.86)	6.02 (0.78)	5.92 (0.90)
4-Dimensional overall	4.09 (0.65)	4.07 (0.66)	4.21 (0.52)	4.14 (0.57)
Competence	4.46 (0.57)	4.49 (0.69)	4.57 (0.50)	4.62 (0.44)
Integrity	4.12 (0.75)	4.07 (0.72)	4.20 (0.65)	4.12 (0.69)
Benevolence	3.96 (0.74)	3.85 (0.74)	4.09 (0.68)	4.03 (0.73)
Openness	3.80 (0.94)	3.88 (0.79)	3.98 (0.78)	3.78 (0.88)
Science article selection (prop.)	0.64 (0.22)	0.64 (0.25)	0.63 (0.23)	0.59 (0.26)
Manipulation check items				
Confidence (uncertainty check)	4.31 (0.70)	3.38 (0.79)	4.28 (0.69)	3.49 (1.01)
Felt uncertainty (uncertainty check)	1.69 (1.02)	2.71 (1.03)	1.70 (1.09)	2.48 (1.25)

Note. Static/Low = static framing + low uncertainty; Static/High = static framing + high uncertainty; Dynamic/Low = dynamic framing + low uncertainty; Dynamic/High = dynamic framing + high uncertainty. Means and *SD*s are on original scales: Science Trust-Suspicious Scale (1-7), 4-Dimensional subscales (1-5), SC-IAT D-score (unbounded). Explicit composite is the z-scored average of the two explicit scales (range reflects z-score units). Subscale rows are from the 4-Dimensional Trust in Scientists scale.

Experiment 3 Pre-Registered Results

Manipulation Check

Participants in the high uncertainty condition reported significantly lower confidence ($M = 3.44$, $SD = 0.92$) than those in the low uncertainty condition ($M = 4.29$, $SD = 0.69$), $t(200.37) = 7.87$, $p < .001$, $d = 1.03$ and significantly greater uncertainty (high: $M = 2.58$, $SD = 1.16$; low: $M = 1.70$, $SD = 1.05$), $t(218.86) = -5.99$, $p < .001$, $d = .80$. Taken together, the manipulation of uncertainty was successful.

Participants in the static framing condition rated the science message as significantly more clear ($M = 4.55$, $SD = 0.55$) than those in the dynamic condition ($M = 4.36$, $SD = 0.76$), $t(218.01) = 2.24$, $p = .026$, $d = 0.29$. The two conditions did not differ in their agreement with the science description (static: $M = 4.30$, $SD = 0.82$; dynamic: $M = 4.25$, $SD = 0.83$), $t(223.48) = 0.47$, $p = .640$, $d = 0.06$. The manipulation produced a clarity difference but did not result in differential agreement with the framing content.

Effects of Framing and Uncertainty on Implicit Trust, Explicit Trust, and Behavior

I conducted two-way ANOVAs with framing and uncertainty as between-subjects factors for each primary dependent variable. See full results in Table 15. For implicit trust in science, a significant main effect of framing emerged, surviving Bonferroni correction. Consistent with Experiment 2, dynamic framing was associated with higher implicit trust in science than static framing. Tukey's HSD showed the dynamic/low uncertainty cell differed significantly from the static/low ($p = .002$) and static/high ($p = .027$) cells (see Figure 7). No uncertainty main effect or interaction emerged for implicit trust in science (both *p*s > .13). Framing and uncertainty did not significantly predict the explicit trust composite or science article selection, and no framing × uncertainty interactions emerged for any primary dependent variable (all *p*s > .116). Exploratory ANOVAs on all eight explicit trust subscales similarly yielded no significant effects (all *p*s > .115).

Table 15

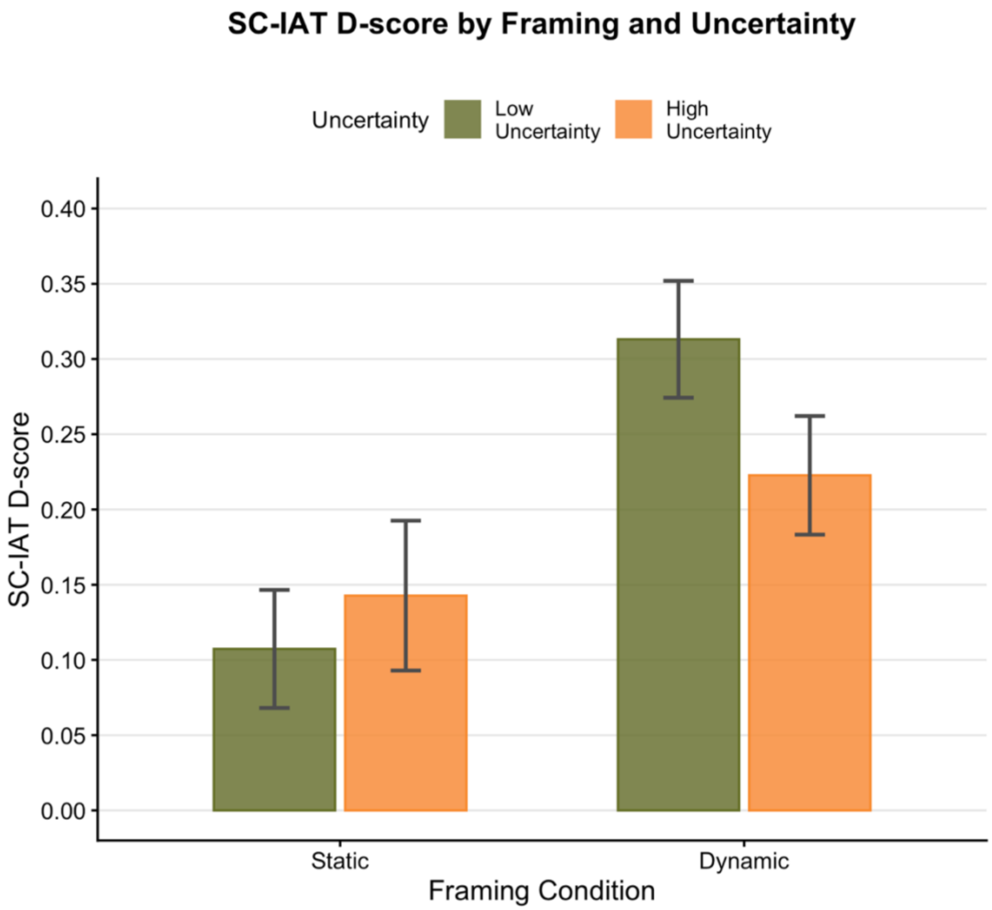
Two-Way ANOVAs: Framing × Uncertainty for Primary Dependent Variables

Predictor	*F*	*p*	$\eta^2 p$
SC-IAT D-score			
Framing	12.11	.001**	.051
Uncertainty	0.58	.446	.003
F × U	2.29	.132	.010
Explicit trust composite			
Framing	0.25	.620	.001
Uncertainty	1.06	.304	.005
F × U	0.01	.923	.000
Science article selection			
Framing	0.83	.362	.004
Uncertainty	0.51	.474	.002
F × U	0.46	.499	.002

Note. $\eta^2 p$ = partial eta-squared. F = Framing, U = Uncertainty. **p* < .05, ***p* < .01.

Figure 7

Interaction Between Framing, Uncertainty, and Implicit Trust in Science



Three-Way Moderated Regression: Objective Scientific Knowledge Accuracy as Moderator

Using objective scientific knowledge accuracy as the moderator, no significant main effects, two-way interactions, or three-way interactions emerged for any primary dependent variable or exploratory subscale (all *ps* > .14). Scientific knowledge accuracy did not moderate the relationship between framing, uncertainty, and any trust or behavioral outcome.

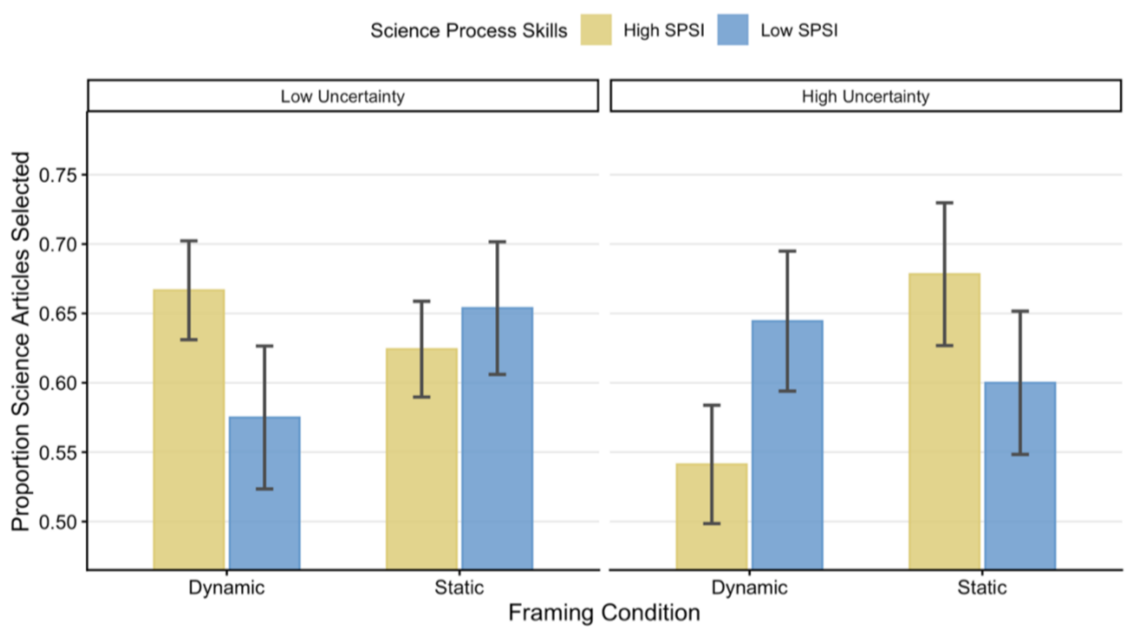
Three-Way Moderated Regression: Science Process Skills Inventory as Moderator

Using the Science Process Skills Inventory as the moderator, several significant and marginal effects emerged. Key regression results are presented in Table 16; simple slopes are summarized in Table 17a and 17b; interaction plots are presented in Figures 8-13.

For science article selection, a significant three-way interaction emerged (see Figure 8). Simple slopes showed that under low uncertainty, framing did not predict science article selection at either Science Process Skills Inventory level (both *p*s > .24). Under high uncertainty, dynamic framing significantly reduced science article selection for participants relatively higher in science process skills (b = -0.16, p = .031) but had no effect for participants relatively lower in science process skills (b = 0.05, p = .473). This pattern suggests the combination of high uncertainty and dynamic framing specifically undermined behavioral engagement with science among those with stronger science process skills.

Figure 8

Interaction Between Science Process Skills Inventory, Uncertainty, Framing, and Science Article Selection



Note. SPSI = Science Process Skills Inventory.

For explicit trust outcomes, a consistent pattern emerged across multiple measures: high uncertainty significantly reduced the explicit trust composite for participants with relatively lower science process skills but not for participants with relatively higher levels of science process skills. For the explicit trust composite, high uncertainty significantly reduced trust for participants with lower science process skills (b = -0.34, p = .047) but not for participants with higher science process skills (b = 0.09, p = .621; see Figure 9). Parallel patterns emerged for the explicit science trust-suspicious scale (b = -0.32, p = .046 at lower science process skills; see Figure 10), the explicit 4-dimensional trust in scientists scale overall score (b = -0.19, p = .085 at lower science process skills; see Figure 11), perceived benevolence ($b = -0.32$, $p = .016$ at lower science process skills; see Figure 12), and perceived competence (see Figure 13). Taken together, science skills buffered participants against the trust-reducing effects of uncertainty across multiple explicit trust dimensions.

Table 16

Three-Way Moderated Regression: Key Models Using Science Process Skills Inventory as Moderator

Predictor	*b (SE)*	*t*	*p*	Model
Explicit trust composite				
Uncertainty	-2.05 (1.00)	-2.05	.041*	R^2 = .069
Framing	-0.47 (0.87)	-0.55	.586	*p* = .025*
SPSI sum	0.01 (0.02)	0.28	.777	
Uncertainty × Framing	1.38 (1.29)	1.07	.286	
Uncertainty × SPSI	0.06 (0.03)	1.96	.052†	
Framing × SPSI	0.02 (0.03)	0.62	.536	
U × F × SPSI	-0.04 (0.04)	-1.12	.266	
Science article selection (three-way p = .013)*				
Uncertainty	-0.47 (0.26)	-1.80	.073†	R^2 = .037
Framing	-0.31 (0.23)	-1.38	.169	*p* = .295
SPSI sum	-0.004 (0.01)	-0.79	.428	
Uncertainty × Framing	0.78 (0.33)	2.33	.021*	
Uncertainty × SPSI	0.01 (0.01)	1.83	.068†	
Framing × SPSI	0.01 (0.01)	1.37	.171	
U × F × SPSI	-0.03 (0.01)	-2.51	.013*	
Competence (exploratory)				
Uncertainty	-1.43 (0.59)	-2.42	.017*	R^2 = .058
Framing	-0.29 (0.52)	-0.57	.568	*p* = .064†
SPSI sum	-0.01 (0.01)	-0.47	.638	
Uncertainty × Framing	1.30 (0.76)	1.71	.088†	
Uncertainty × SPSI	0.05 (0.02)	2.52	.013*	
Framing × SPSI	0.01 (0.02)	0.79	.433	
U × F × SPSI	-0.04 (0.02)	-1.75	.081†	
Benevolence (exploratory)				
Uncertainty	-1.53 (0.77)	-1.99	.048*	R^2 = .067
Framing	-0.01 (0.67)	-0.02	.988	*p* = .032*
SPSI sum	-0.002 (0.02)	-0.16	.877	
Uncertainty × Framing	0.40 (0.99)	0.40	.689	
Uncertainty × SPSI	0.05 (0.02)	1.88	.061†	
Framing × SPSI	0.004 (0.02)	0.21	.833	
U × F × SPSI	-0.01 (0.03)	-0.40	.693	

Note. SPSI = Science Process Skills Inventory sum score, F = Framing, U = Uncertainty. *p < .05. †p < .10.

Table 17A
Simple Slopes for Three-Way Interactions

Uncertainty Condition	Framing	SPSI Level	*M* (*SD*)	*b* (*SE*)	*p*
Outcome: Science article selection					
Low uncertainty	Dynamic	High SPSI (+1 SD)	.67 (.21)	.05 (.06)	.362
		Low SPSI (-1 SD)	.58 (.25)	-.07 (.06)	.249
	Static	High SPSI (+1 SD)	.62 (.20)	-.05 (.06)	.362
		Low SPSI (-1 SD)	.65 (.24)	.07 (.06)	.249
High uncertainty	Dynamic	High SPSI (+1 SD)	.54 (.25)	-.16 (.07)	.031*
		Low SPSI (-1 SD)	.64 (.26)	.05 (.07)	.473
	Static	High SPSI (+1 SD)	.68 (.25)	.16 (.07)	.031*
		Low SPSI (-1 SD)	.60 (.26)	-.05 (.07)	.472
Outcome: Perceived competence					
Low uncertainty	Dynamic	High SPSI (+1 SD)	4.61 (.45)	.18 (.14)	.200
		Low SPSI (-1 SD)	4.50 (.58)	.02 (.14)	.860
	Static	High SPSI (+1 SD)	4.39 (.62)	-.18 (.14)	.200
		Low SPSI (-1 SD)	4.55 (.51)	-.02 (.14)	.860
High uncertainty	Dynamic	High SPSI (+1 SD)	4.65 (.43)	-.09 (.15)	.567
		Low SPSI (-1 SD)	4.58 (.46)	.28 (.15)	.070†
	Static	High SPSI (+1 SD)	4.72 (.45)	.09 (.15)	.567
		Low SPSI (-1 SD)	4.28 (.81)	-.28 (.15)	.070†

*Note***.** *M* and *SD* are based on a median split of SPSI for descriptive purposes. *b* = unstandardized regression coefficient from continuous-SPSI simple slopes models re-centered at ±1 *SD*. *SE* = standard error. SPSI = Science Process Skills Inventory. †$p < .10$. *$p < .05$.

Table 17B
Simple Slopes for Two-Way Interactions

Uncertainty Condition	SPSI Level	*M* (SD)	*b* (SE)	*p*
Outcome: Explicit trust composite				
High uncertainty	High SPSI (+1 SD)	.17 (.81)	.09 (.17)	.621
	Low SPSI (-1 SD)	-.33 (1.06)	-.34 (.17)	.047*
Low uncertainty	High SPSI (+1 SD)	.11 (.97)	-.09 (.17)	.621
	Low SPSI (-1 SD)	-.01 (.83)	.34 (.17)	.047*
Outcome: Trust-Suspicious Scale				
High uncertainty	High SPSI (+1 SD)	6.07 (.77)	.00 (.16)	.998
	Low SPSI (-1 SD)	5.72 (.96)	-.32 (.16)	.046*
Low uncertainty	High SPSI (+1 SD)	6.11 (.88)	.00 (.16)	.998
	Low SPSI (-1 SD)	5.99 (.75)	.32 (.16)	.046*
Outcome: 4-Dimensional overall				
High uncertainty	High SPSI (+1 SD)	4.28 (.53)	.10 (.11)	.356
	Low SPSI (-1 SD)	3.92 (.64)	-.19 (.11)	.085†
Low uncertainty	High SPSI (+1 SD)	4.17 (.62)	-.10 (.11)	.356
	Low SPSI (-1 SD)	4.12 (.54)	.19 (.11)	.085†
Outcome: Perceived benevolence				
High uncertainty	High SPSI (+1 SD)	4.15 (.74)	.17 (.13)	.203
	Low SPSI (-1 SD)	3.73 (.68)	-.32 (.13)	.016*
Low uncertainty	High SPSI (+1 SD)	3.98 (.80)	-.17 (.13)	.203
	Low SPSI (-1 SD)	4.09 (.56)	.32 (.13)	.016*

Note. *M* and *SD* are based on a median split of SPSI for descriptive purposes; means are collapsed across framing condition. *b* = unstandardized regression coefficient from continuous-SPSI simple slopes models re-centered at ±1 *SD*. *SE* = standard error. SPSI = Science Process Skills Inventory. †$p < .10$. *$p < .05$.

Figure 9

Interaction Between Science Process Skills Inventory, Uncertainty, and Explicit Trust Composite

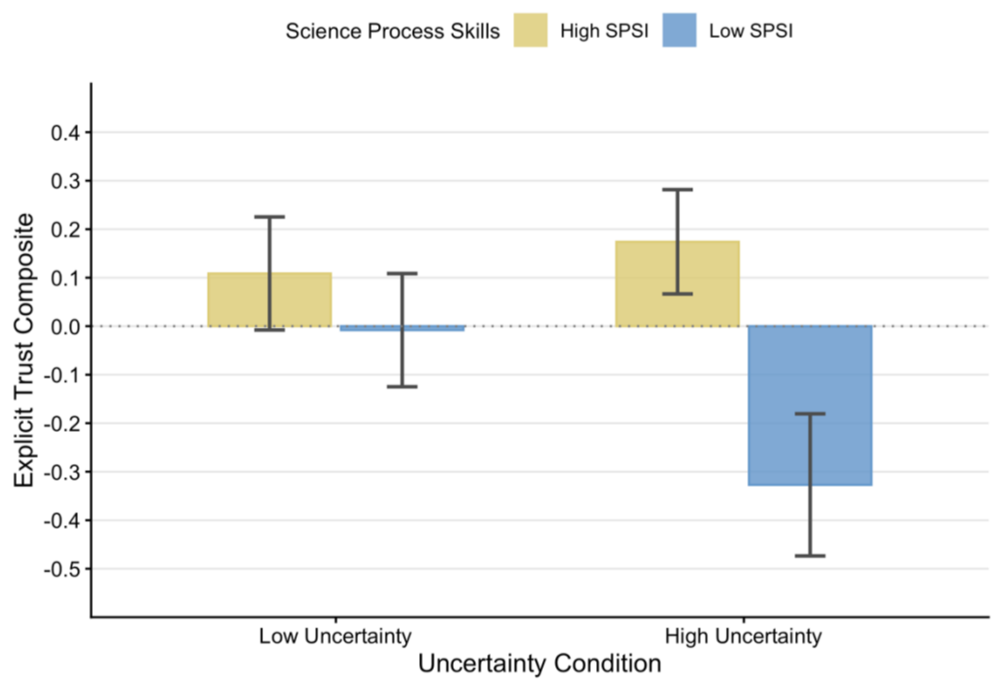


Figure 10

Interaction Between Science Process Skills Inventory, Uncertainty, and Explicit Science Trust-Suspicious Scale

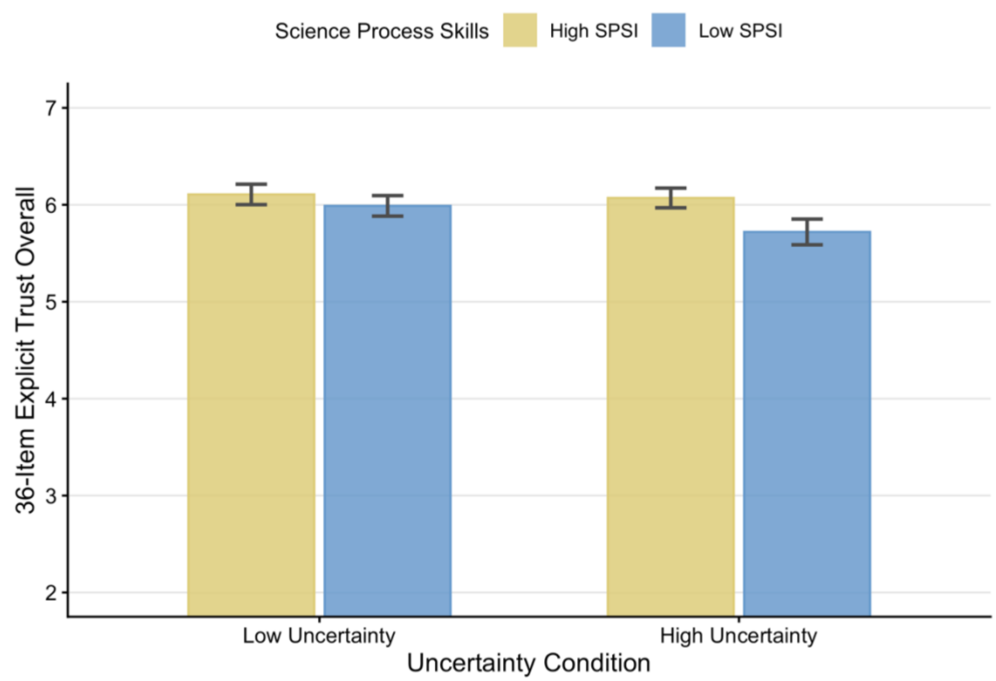


Figure 11

Interaction Between Science Process Skills Inventory, Uncertainty, and Explicit 4-Dimensional Overall Trust in Scientists

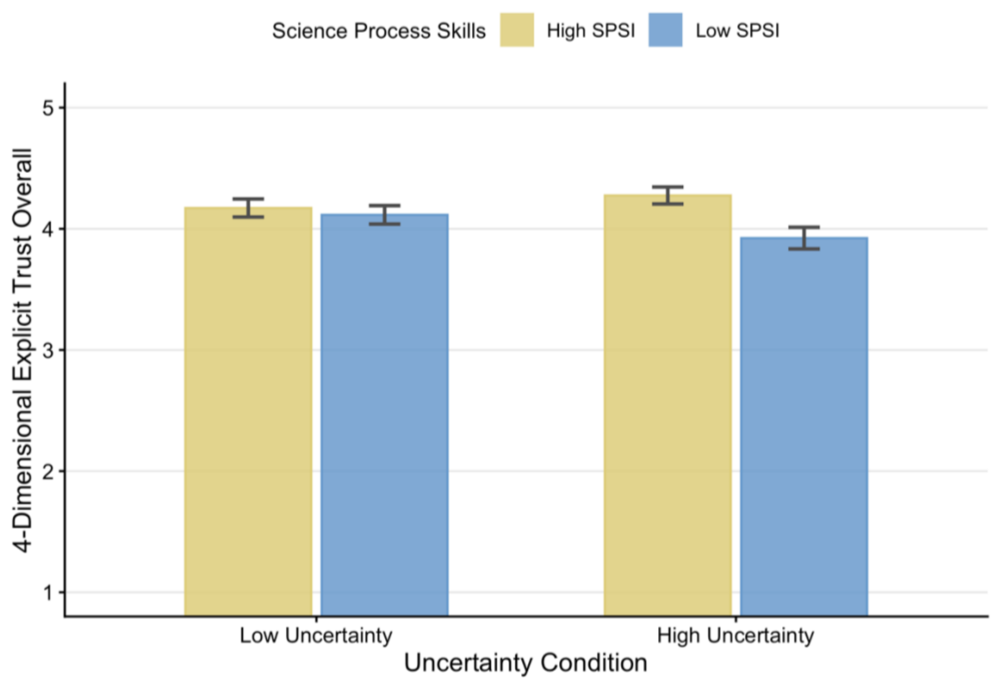


Figure 12

Interaction Between Science Process Skills Inventory, Uncertainty, and Perceived Benevolence

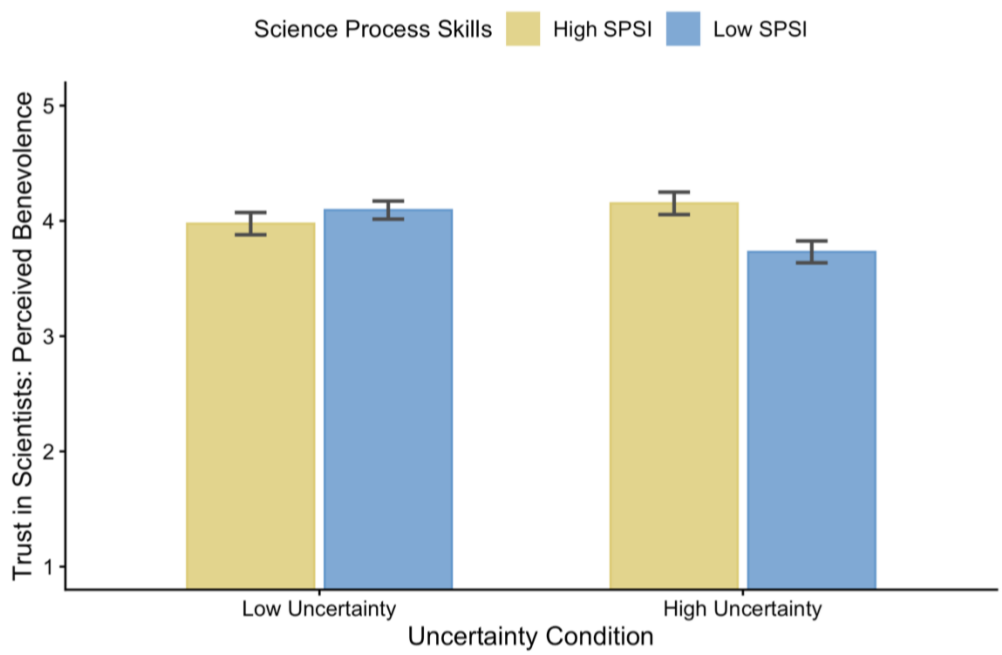
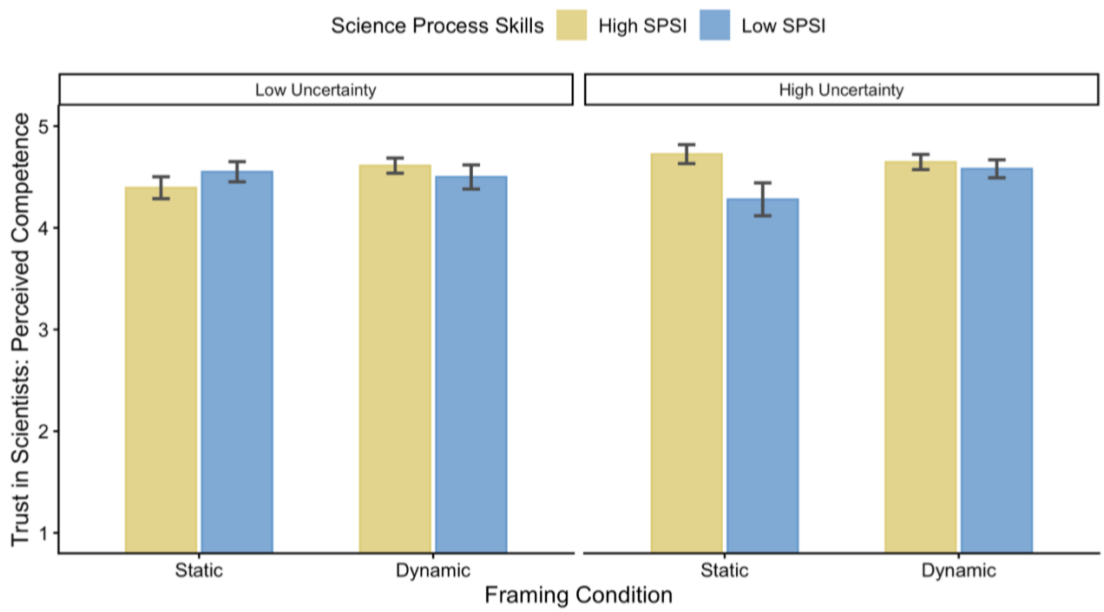


Figure 13

Interaction Between Framing, Science Process Skills Inventory, Uncertainty, and Perceived Competence



Experiment 3 Discussion

Dynamic framing again produced higher implicit trust in science than static framing, replicating the pattern from Experiment 2 across both uncertainty conditions. Science skills moderated the effect of uncertainty on the explicit trust composite and behavior: participants with lower science process skills showed significantly lower trust under high uncertainty, while those with higher science process skills were largely buffered against these effects. The three-way interaction on science article selection suggests that under high uncertainty, dynamic framing specifically reduced behavioral engagement among participants with higher science process skills, possibly because they were more sensitive to the implications of evolving scientific knowledge. No three-way interaction patterns emerged for implicit trust in science or the explicit trust composite. These findings highlight the effects of framing on implicit trust in science and that science skills act as a meaningful individual difference in how people respond to scientific uncertainty.

Exploratory Analyses

In addition to the pre-registered confirmatory analyses reported above, I conducted three sets of exploratory analyses to build a more complete picture of the constructs and patterns within my dissertation. First, I assessed the validity and reliability of the measures used across all three experiments which is important to consider when interpreting the primary findings. Second, I examined how demographic variables related to the primary dependent variables across experiments and whether they moderated the primary experimental effects, motivated by growing evidence that trust in science is deeply tied to some social group memberships (i.e. political identity). Third, I conducted a mini meta-analysis synthesizing effect sizes across all three experiments with the goal of identifying which effects are robust and replicable across experimental contexts and which are sensitive to contextual variation.

Cross-Experiment Validation and Reliability

First, to assess the validity and reliability of the scales used across experiments, I calculated the split-half reliability (odd vs. even trials, Spearman-Brown corrected) from trial-level SC-IAT data. *N*s for reliability estimates = 108, 202, and 281 for Experiments 1, 2, and 3, respectively (larger than analytic sample due to inclusion of all participants prior to exclusions; see Table 18). The split-half reliability ranged from .77-.79 which is consistent with, and even slightly above, the published SC-IAT reliabilities of .50-.70 (Karpinski & Steinman, 2006).

I also calculated Cronbach's alpha for the explicit measures, scientific process skills inventory, and all filler task scales. For the explicit science trust-suspicious scale, α = .97 - .98, indicating high reliability. For the 4-dimensional trust in scientists overall scale, α = .91 - .93, indicating high reliability. For each of the subscales, α = .79 - .90 indicating slightly lower but still relatively high reliability given the subscales are only 3 questions. For the Science Process Skills Inventory, α = .92 - .93 indicating high reliability. For the NFC, α = .90 - .92 indicating high reliability. For the PANAS, α = .91 - .94 indicating high reliability. For the BFI-10, α = .37 - .84 indicating low to acceptable reliability. However, the BFI-10 subscales contain only 2 items per trait, therefore low α values are expected given the scale's brevity.

Table 18

Scale Reliability Across All Three Experiments

Scale	Items	Exp. 1	Exp. 2	Exp. 3
Implicit Trust in Science				
SC-IAT (split-half SB-r)†		.79	.79	.77
Explicit Trust in Science				
Science Trust-Suspicious Scale	36	.97	.97	.98
4-Dimensional Trust in Scientists (overall)	12	.91	.93	.92
Competence	3	.81	.87	.86
Integrity	3	.90	.88	.89
Benevolence	3	.87	.88	.83
Openness	3	.79	.83	.85
Scientific Skills				
Science Process Skills Inventory (SPSI)	11	.93	.93	.92
Individual Difference Measures				
Need for Cognition (NFC)	6	.90	.91	.92
PANAS: Positive Affect	10	.91	.91	.93
PANAS: Negative Affect	10	.92	.91	.94
Big Five Personality (BFI-10)‡				
Extraversion	2	.59	.74	.73
Agreeableness	2	.45	.57	.56
Conscientiousness	2	.37	.48	.58
Neuroticism	2	.84	.76	.81
Openness	2	.40	.52	.56

Note. Unless otherwise noted, values are Cronbach's α. Interpretation benchmarks: ≥ .90 = excellent, ≥ .80 = good, ≥ .70 = acceptable, ≥ .60 = questionable, < .60 = poor (George & Mallery, 2003). SB-*r* = Spearman-Brown corrected split-half reliability. †Cronbach's α is not appropriate for reaction time measures.

SC-IAT Validity Checks Across Three Experiments

I also conducted two validity checks for the SC-IAT across all three experiments: (1) a one-sample *t*-test confirming that mean *D*-scores were significantly greater than zero, indicating that participants reliably associated science with trustworthiness at the implicit level, and (2) a condition order check confirming that block order (trustworthy-science first vs. suspicious-science first) did not significantly bias implicit trust in science scores.

SC-IAT D-Score Distribution: One-Sample t-Tests Against Zero

Across all three experiments, mean SC-IAT *D*-scores were significantly greater than zero (*t*s = 2.94, 5.02, 9.41; all *p*s ≤ .004; *d*s = 0.30, 0.38, 0.62), with the majority of participants showing positive *D*-scores increasing across experiments (57.1%, 63.7%, 74.6%). See full results in Table 19.

Table 19

SC-IAT D-score Distribution: One-Sample t-Tests Against Zero

Experiment	*N*	*M (SD)*	% > 0	*t*	*p*	*d*
Experiment 1	98	0.09 (.32)	57.1%	2.94	.004**	0.30
Experiment 2	171	0.13 (.33)	63.7%	5.02	< .001***	0.38
Experiment 3	228	0.20 (.32)	74.6%	9.41	< .001***	0.62

Note. **p < .01. ***p < .001.

SC-IAT Condition Order Check

Condition order did not significantly influence implicit trust in science scores in any experiment (all *p*s > .22), and effect sizes were small (|*d*|s = 0.25, 0.12, 0.16). The direction of the order effect was not consistent across experiments; Trustworthy-Science first participants showed slightly higher scores in Experiments 1 and 2, while Suspicious-Science first participants showed slightly higher scores in Experiment 3, suggesting the small numerical differences reflect sampling variability rather than a systematic order artifact. These results support the reliability and statistical validity of the SC-IAT as a measure of implicit trust in science in the present samples (see Table 20).

Table 20

SC-IAT Condition Order Check: D-scores by Block Order Across Three Studies

Experiment	Trustworthy-Science First *M* (*SD*)	*n*	Suspicious-Science First *M* (*SD*)	*n*	*t*	*p*	*d*
Experiment 1	0.134 (0.327)	48	0.056 (0.307)	50	1.21	.229	0.25
Experiment 2	0.145 (0.328)	85	0.106 (0.327)	86	0.78	.437	0.12
Experiment 3	0.174 (0.337)	114	0.226 (0.303)	114	-1.22	.225	-0.16

Note. Trustworthy-Science first = trustworthy-science block administered before suspicious-science block; Suspicious-Science First = suspicious-science block administered first.

Exploratory Demographic Analyses

Next, I ran exploratory analyses examining if political orientation, gender, religion, and education were associated with implicit trust in science, the explicit trust composite, and science article selection across all three experiments. I also tested whether any of these variables moderated the primary trust-behavior relationships in Experiment 1 and the framing and uncertainty effects in Experiments 2 and 3.

I conducted Pearson correlations for continuous demographics (political views, education, political interest), one-way ANOVAs for categorical demographics with three or more groups, and independent-samples *t*-tests for gender. In Experiment 1, I also tested whether each demographic variable moderated the implicit trust in science → behavior and explicit trust composite → behavior relationships. In Experiments 2 and 3, I tested whether each demographic variable moderated the primary experimental effects (framing in Experiment 2; framing and uncertainty in Experiment 3). All tests are two-tailed and exploratory; I did not apply corrections for multiple comparisons.

I also want to note that I coded religion in two ways throughout the exploratory analyses. The three-category breakdown distinguishes between Christians, non-religious participants (atheist, agnostic, or no religious affiliation), and all other religious affiliations combined as "other religion" (Buddhist, Hindu, Jewish, Muslim, or other specified religion). The two-category collapse combines Christians and other religion participants into a single "Religious" group, contrasted with the non-religious group. Since Christianity specifically is associated with lower trust in science (Scheitle et al., 2025), I wanted to look at the distinct group differences. That said, the other religion cell is too small (n = 9-10 across experiments) to support stable estimates as a standalone group, which is why I also collapsed into two broad categories.

Correlations with Primary Dependent Variables

Across all three experiments, political views showed a consistent and significant negative correlation with the explicit trust composite, indicating that more conservative participants reported lower explicit trust in science (Experiment 1: $r = -.29$, $p = .004$;

Experiment 2: $r = -.26$, $p = .001$; Experiment 3: $r = -.41$, $p < .001$). Political views were not significantly associated with implicit trust in science in any experiment (all ps > .15). In Experiments 1 and 2, political views were also not significantly associated with science article selection; however, in Experiment 3, a significant negative correlation emerged ($r = -.16$, $p = .017$).

Across all three experiments, political interest also showed a pattern of association with the primary dependent variables. In Experiment 1, political interest showed a marginal positive association with the explicit trust composite ($r = .18$, $p = .074$) but was not significantly correlated with implicit trust in science or science article selection. In Experiments 2 and 3, political interest was significantly positively correlated with all three primary dependent variables, suggesting that greater political engagement is a reliable individual difference associated with stronger trust in science and more science-oriented behavioral choices. Education was not significantly correlated with any primary dependent variable across any of the three experiments. See full results in Table 21.

Table 21

Cross-Experiment Correlations Between Continuous Demographics and Primary Dependent Variables

		Exp. 1		*Exp. 2*		*Exp. 3*	
Demographic	**Measure**	*r*	*p*	*r*	*p*	*r*	*p*
Political views	SC-IAT	.15	.155	-.01	.895	-.04	.571
	Explicit trust composite	-.29	.004**	-.26	.001**	-.41	<.001***
	Science article selection	-.03	.768	-.09	.233	-.16	.017*
Education	SC-IAT	.07	.477	.03	.694	.06	.385
	Explicit trust composite	.12	.230	-.12	.128	.11	.095†
	Science article selection	.14	.163	.06	.476	.06	.345
Political interest	SC-IAT	.17	.101	.17	.028*	.15	.021*
	Explicit trust composite	.18	.074†	.17	.027*	.27	<.001***
	Science article selection	.07	.527	.17	.023*	.16	.016*

Note. Political views coded 1 (very liberal) to 7 (very conservative). Education coded numerically (1-6; higher = more education). Political interest coded 1 (not at all) to 7 (extremely). †$p < .10$. *$p < .05$. **$p < .01$. ***$p < .001$.

Demographic Differences in Explicit Trust

Political party consistently predicted the explicit trust composite across all three experiments: Experiment 1 $F(2, 90) = 5.73$, $p = .005$, $\eta^2 = .11$; Experiment 2 $F(2, 163) = 12.98$, $p < .001$, $\eta^2 = .14$; Experiment 3 $F(2, 222) = 22.76$, $p < .001$, $\eta^2 = .17$, see Figure

14. Across the three experiments, Democrats reported higher explicit trust than both Independents/Others and Republicans in every sample. Political views showed a similar pattern, with liberals reporting higher explicit trust than conservatives in all three experiments: Experiment 1 $F(2, 85) = 11.68$, $p < .001$, $\eta^2 = .22$; Experiment 2 $F(2, 162) = 9.33$, $p < .001$, $\eta^2 = .10$; Experiment 3 $F(2, 218) = 16.41$, $p < .001$, $\eta^2 = .13$, see Figure 15.

Both three-category and two-category religion also significantly predicted the explicit trust composite in all three experiments, with non-religious participants reporting higher explicit trust than Christians and religious participants in every sample, respectively (see Figure 16 for three-category religion and Figure 17 for two-category religion). Gender and education did not significantly predict the explicit trust composite in any experiment (all *p*s > .24). See full results in Table 22.

Table 22

Cross-Experiment Group Comparisons on Explicit Trust Composite

Demographic	*Exp. 1*	*Exp. 2*	*Exp. 3*
Political party			
Democrat	.31 (.60)	.39 (.59)	.39 (.61)
Independent/Other	-.12 (1.02)	-.35 (1.10)	-.14 (.84)
Republican	-.37 (.97)	-.23 (.98)	-.53 (1.17)
Model	$p = .005$**, $\eta^2 = .11$	$p < .001$***, $\eta^2 = .14$	$p < .001$***, $\eta^2 = .17$
Political views			
Liberal	.42 (.57)	.28 (.69)	.26 (.69)
Moderate	-.44 (1.08)	-.07 (.88)	.06 (.83)
Conservative	-.33 (.90)	-.41 (1.17)	-.51 (1.16)
Model	$p < .001$***, $\eta^2 = .22$	$p < .001$***, $\eta^2 = .10$	$p < .001$***, $\eta^2 = .13$
Religion (3-category)			
Christian	-.22 (.90)	-.22 (1.03)	-.09 (1.03)
Non-religious	.40 (.69)	.27 (.72)	.17 (.74)
Other religion	.25 (.53)	-.27 (1.04)	-.36 (.92)
Model	$p = .002$**, $\eta^2 = .13$	$p = .002$**, $\eta^2 = .07$	$p = .040$*, $\eta^2 = .03$
Religion (2-category)			
Non-religious	.40 (.69)	.267 (.72)	.17 (.74)
Religious	-.15 (.87)	-.229 (1.03)	-.12 (1.02)
Model	$p = .001$**, $d = .56$	$p < .001$***, $d = .55$	$p = .015$*, $d = .32$
Gender			
Man	.15 (.73)	-.05 (1.12)	.03 (.80)
Woman	-.05 (.97)	.03 (.74)	-.02 (1.06)
Model	$p = .246$, $d = 0.25$	$p = .627$, $d = 0.08$	$p = .711$, $d = 0.05$
Education (3-category)			
Bachelor's or higher	.15 (.82)	-.09 (1.06)	.06 (.91)
Some college	-.06 (.89)	.05 (.78)	-.02 (.95)
HS or less	-.18 (1.18)	.19 (.72)	-.18 (1.05)
Model	$p = .418$, $\eta^2 = .02$	$p = .391$, $\eta^2 = .01$	$p = .477$, $\eta^2 = .01$

Note. Values are *M* (*SD*) for the z-scored explicit trust composite. Religion is presented with both a 3-category breakdown (Christian / Non-religious / Other religion) and a 2-category collapse (Non-religious vs. Religious). *$p < .05$. **$p < .01$. ***$p < .001$.

Figure 14

Explicit Trust Composite by Political Party Across All Three Experiments

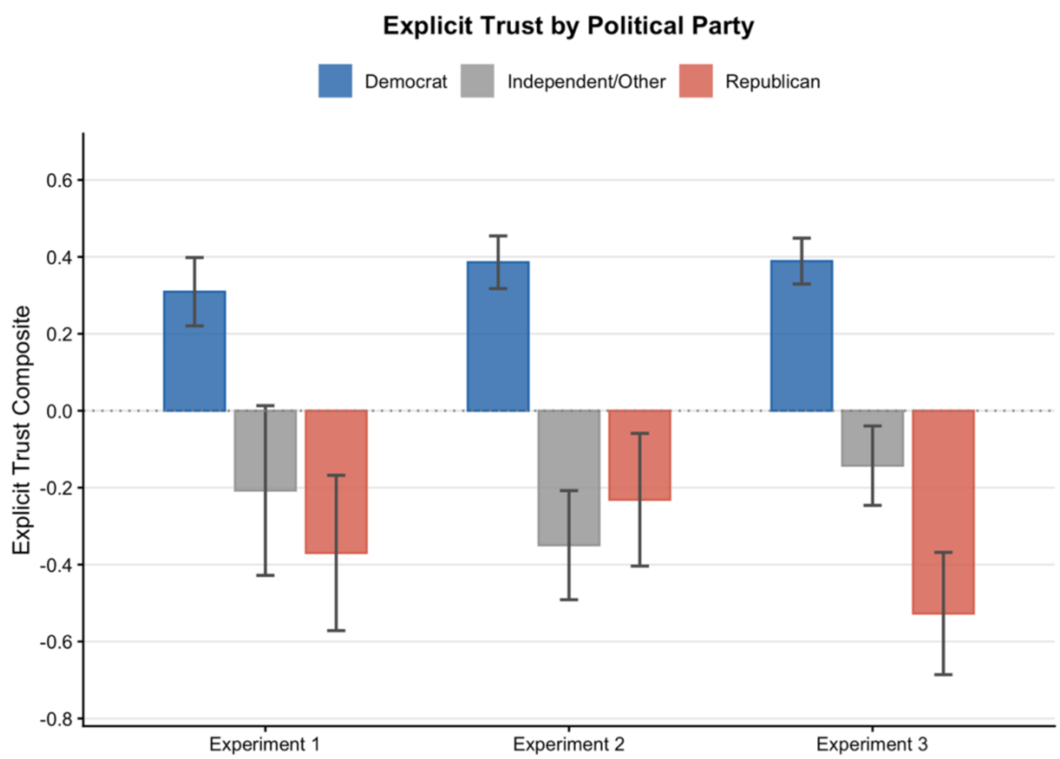


Figure 15

Explicit Trust Composite by Political Views Across All Three Experiments

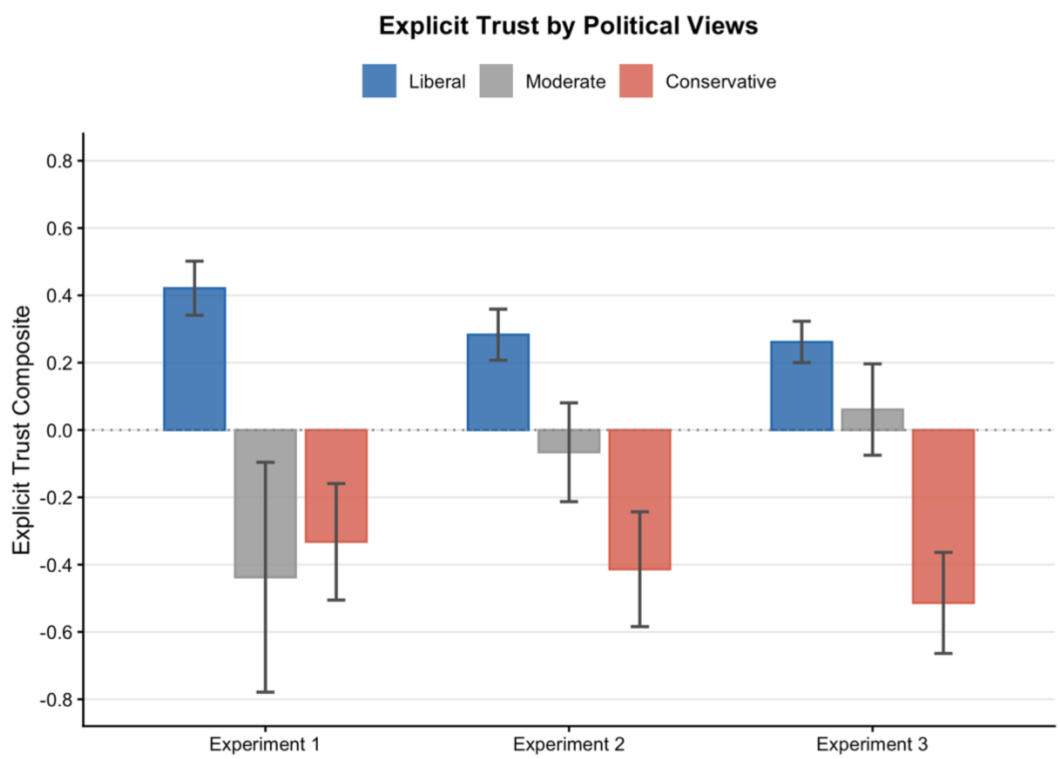


Figure 16

Explicit Trust Composite by Three-Category Religion Across All Three Experiments

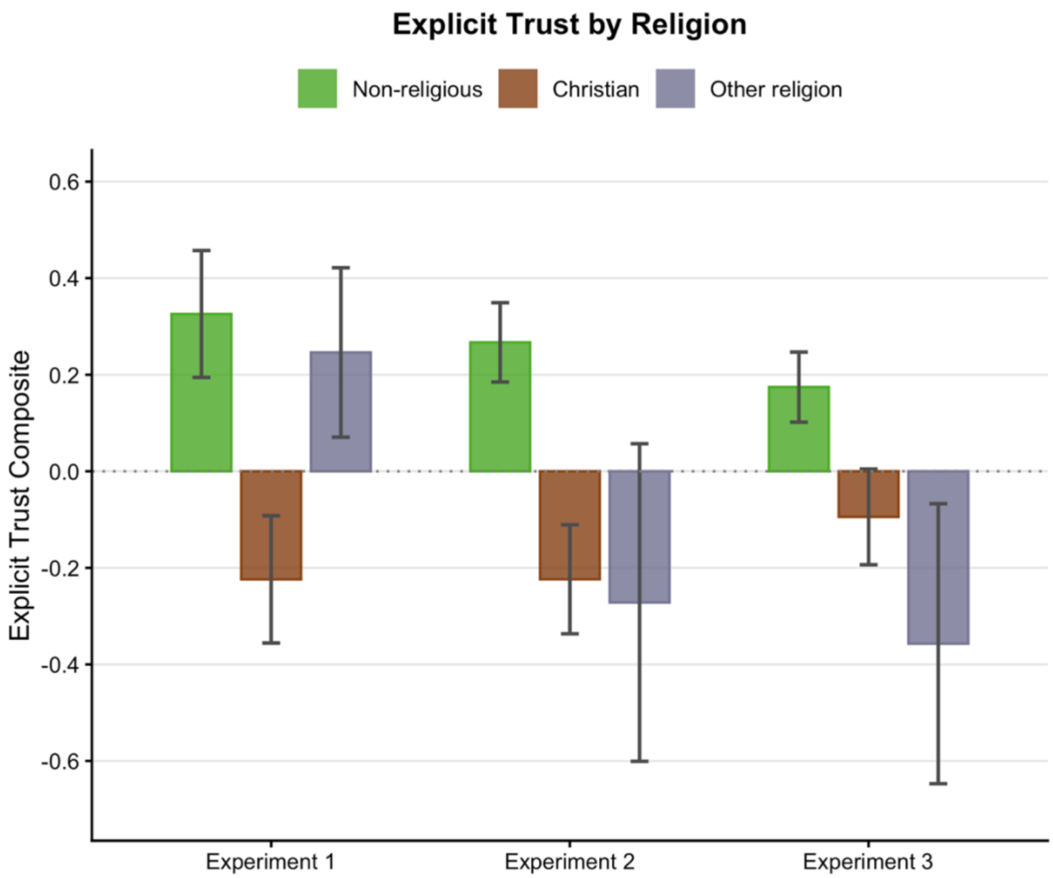
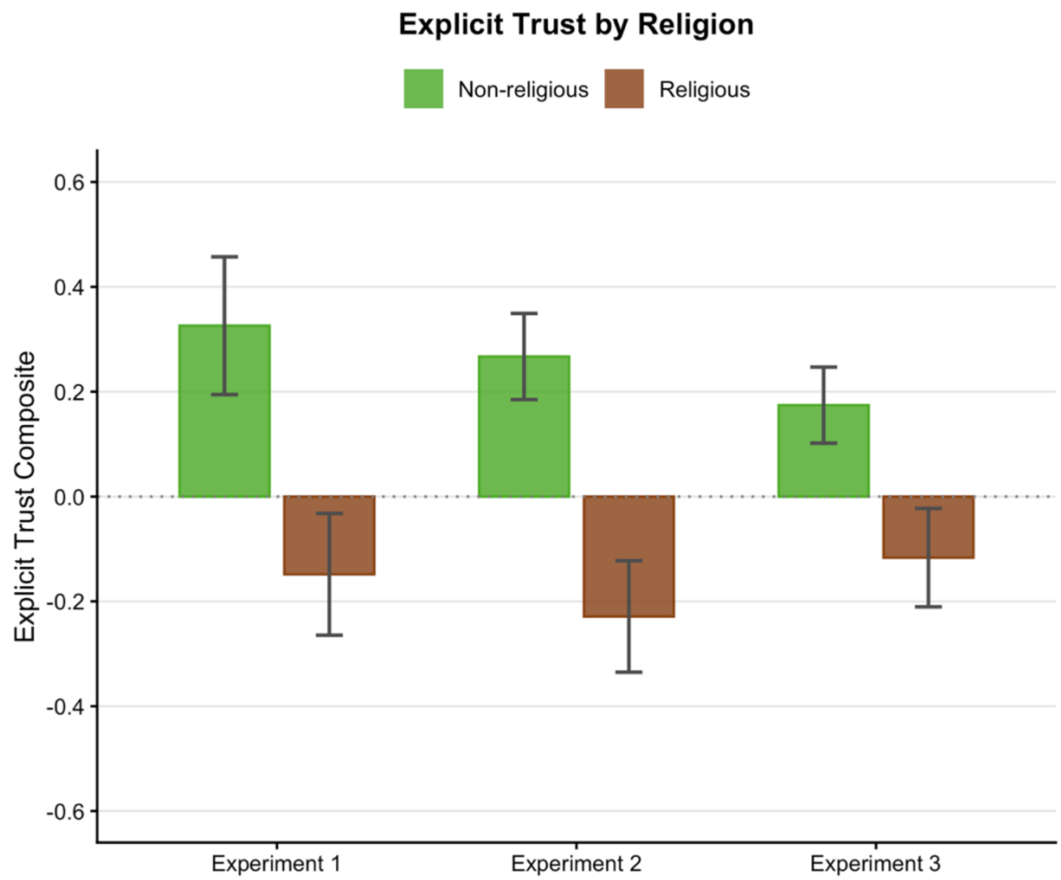


Figure 17

Explicit Trust Composite by Two-Category Religion Across All Three Experiments



Demographic Differences in Implicit Trust in Science

No demographic variable significantly predicted implicit trust in science in any of the three experiments (all *p*s > .12). This pattern was consistent: political party, political views, religion, gender, and education produced no significant differences in SC-IAT *D*-scores across any of the experiments. This pattern stands in contrast to the robust demographic effects on the explicit trust composite. See full results in Table 23 and Figures 18-21.

Table 23

Cross-Experiment Group Comparisons on Implicit Trust in Science (SC-IAT D-Score)

Demographic	*Exp. 1*	*Exp. 2*	*Exp. 3*
Political party			
Democrat	.17 (.28)	.13 (.29)	.22 (.32)
Independent/Other	.04 (.35)	.11 (.37)	.22 (.32)
Republican	.08 (.27)	.17 (.31)	.14 (.33)
Model	p = .122, η^2 = .05	p = .699, η^2 = .00	p = .314, η^2 = .01
Political views			
Liberal	.10 (.30)	.14 (.32)	.23 (.31)
Moderate	.13 (.28)	.08 (.34)	.22 (.28)
Conservative	.16 (.30)	.14 (.30)	.15 (.34)
Model	p = .429, η^2 = .02	p = .582, η^2 = .01	p = .236, η^2 = .01
Religion (3-category)			
Christian	.089 (.344)	.117 (.336)	.175 (.337)
Non-religious	.108 (.269)	.135 (.311)	.232 (.302)
Other religion	.133 (.373)	.206 (.331)	.064 (.263)
Model	p = .917, η^2 = .002	p = .704, η^2 = .004	p = .171, η^2= .02
Religion (2-category)			
Non-religious	.108 (.269)	.135 (.311)	.232 (.302)
Religious	.096 (.346)	.126 (.335)	.166 (.332)
Model	p = .860, d = -.05	p = .867, d = .03	p = .118, d = .21
Gender			
Man	.11 (.29)	.14 (.33)	.22 (.34)
Woman	.10 (.35)	.12 (.32)	.17 (.30)
Model	p = .842, d = 0.04	p = .783, d = 0.04	p = .276, d = 0.15
Education (3-category)			
Bachelor's or higher	.10 (.32)	.15 (.28)	.20 (.32)
Some college	.14 (.33)	.10 (.40)	.22 (.33)
HS or less	-.07 (.16)	.12 (.30)	.13 (.34)
Model	p = .250, η^2 = .03	p = .625, η^2 = .01	p = .493, η^2 = .01

Note. Values are *M* (*SD*) for the SC-IAT *D*-score. Religion presented with 3-category (Christian / Non-religious / Other religion) and 2-category (Non-religious vs. Religious) breakdowns. *p < .05. **p < .01. ***p < .001.

Figure 18

Implicit Trust in Science by Political Party Across All Three Experiments

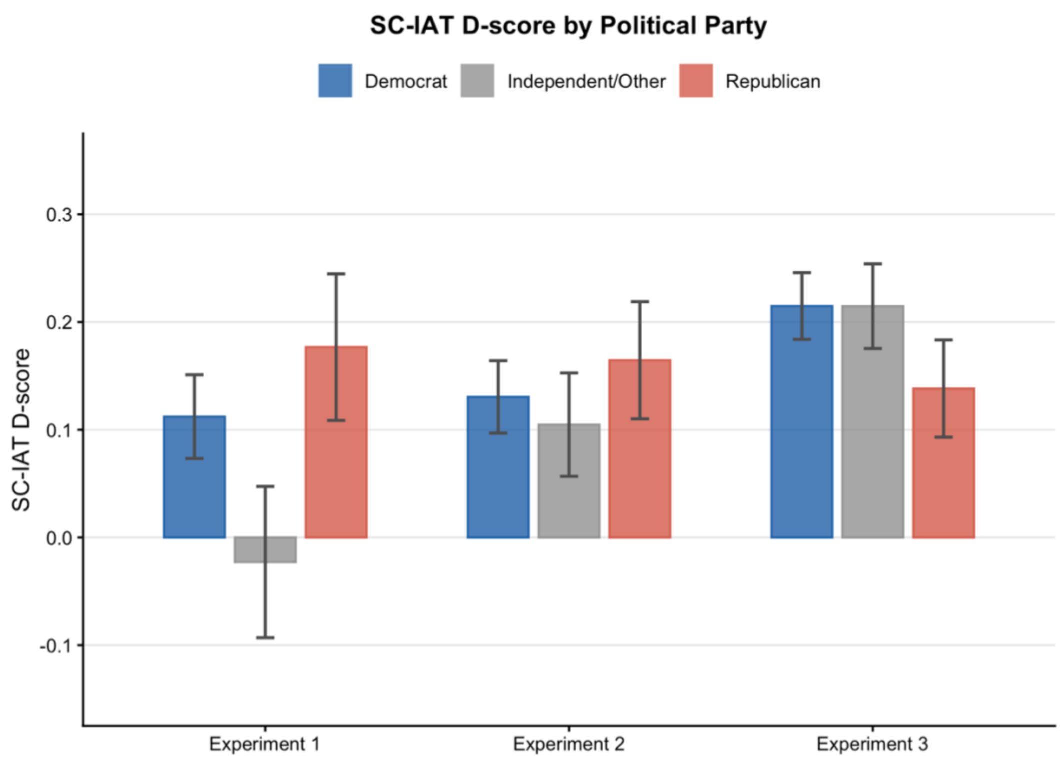


Figure 19

Implicit Trust in Science by Political Views Across All Three Experiments

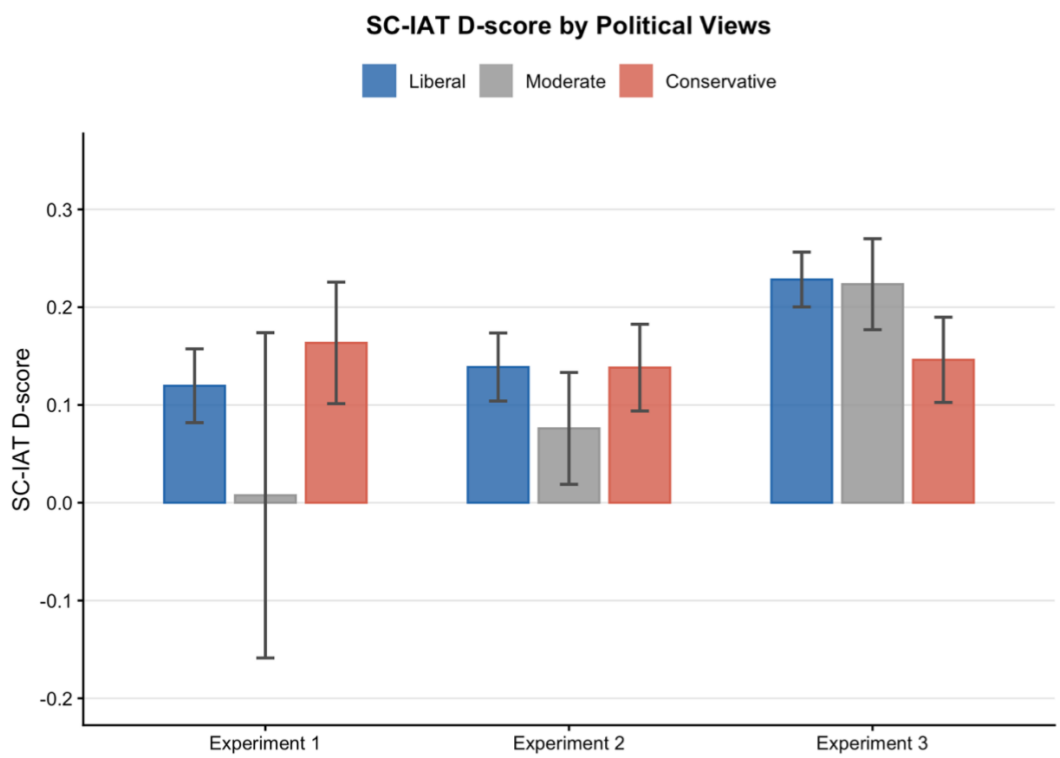


Figure 20

Implicit Trust in Science by Three-Category Religion Across All Three Experiments

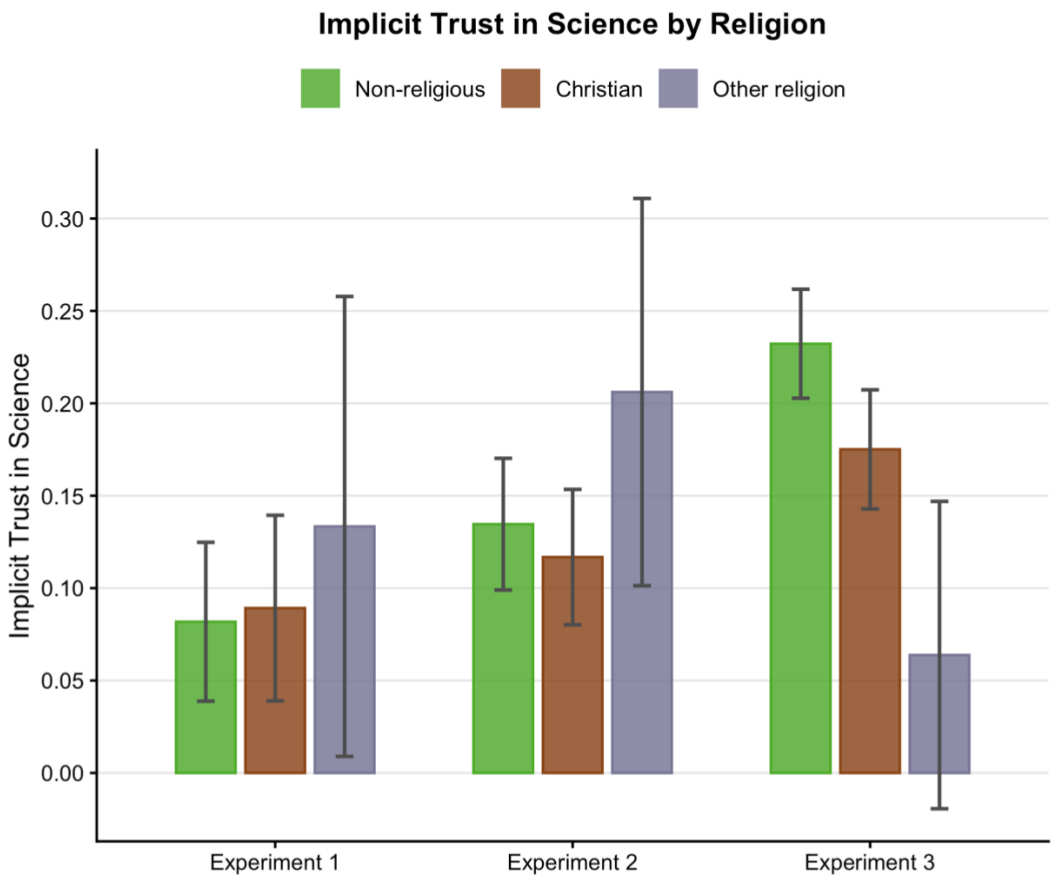
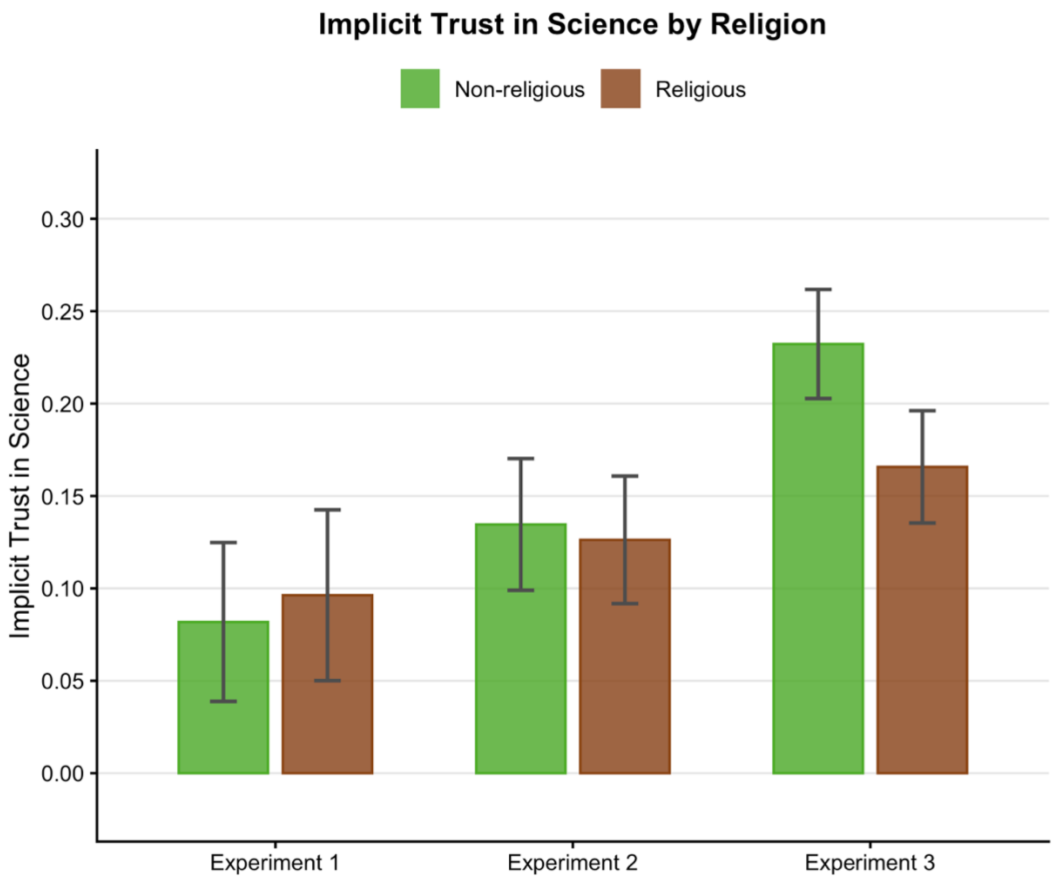


Figure 21

Implicit Trust in Science by Two-Category Religion Across All Three Experiments



Demographic Differences in Science Article Selection

Demographic variables showed minimal and inconsistent associations with science article selection across experiments. In Experiment 1, no demographic variable significantly predicted science article selection (all *p*s > .18). In Experiment 2, two-category religion showed a marginal trend, with non-religious participants selecting slightly more science articles (M = 0.66) than Christians (M = 0.57), $F(2, 167) = 2.37$, $p = .097$; no other demographic variable approached significance. In Experiment 3, religion significantly predicted science article selection ($F(2, 221) = 3.30$, $p = .039$, $\eta^2 = .03$), with non-religious participants selecting more articles (M = 0.66) than Christians (M = 0.60); political views also showed a marginal trend ($F(2, 218) = 2.52$, p = .083), with conservatives selecting fewer articles (M = 0.56) than liberals (M = 0.65) and moderates (M = 0.64). See full results in Table 24 and Figures 22-25.

Table 24

Cross-Experiment Group Comparisons on Science Article Selection

Demographic	*Exp. 1*	*Exp. 2*	*Exp. 3*
Political party			
Democrat	.68 (.24)	.614 (.276)	.64 (.25)
Independent/Other	.58 (.25)	.603 (.219)	.64 (.22)
Republican	.61 (.21)	.600 (.254)	.57 (.25)
Model	p = .184, η^2 = .04	p = .958, η^2 = .00	p = .140, η^2 = .02
Political views			
Liberal	.66 (.25)	.634 (.266)	.65 (.24)
Moderate	.66 (.23)	.633 (.211)	.64 (.24)
Conservative	.60 (.21)	.553 (.261)	.56 (.23)
Model	p = .555, η^2 = .01	p = .186, η^2 = .02	p = .083†, η^2 = .02
Religion (3-category)			
Christian	.630 (.221)	.571 (.260)	.604 (.234)
Non-religious	.647 (.252)	.655 (.252)	.657 (.238)
Other religion	.667 (.283)	.560 (.207)	.480 (.235)
Model	p = .891, η^2 = .002	p = .097†, η^2 = .03	p = .039*, η^2 = .03
Religion (2-category)			
Non-religious	.647 (.252)	.655 (.252)	.657 (.238)
Religious	.636 (.229)	.570 (.254)	.593 (.236)
Model	p = .820, d = .03	p = .031*, d = -.34	p = .045*, d = -.27
Gender			
Man	.62 (.23)	.628 (.256)	.63 (.22)
Woman	.64 (.24)	.591 (.256)	.61 (.26)
Model	p = .590, d = 0.10	p = .356, d = 0.14	p = .489, d = 0.09
Education (3-category)			
Bachelor's or higher	.66 (.26)	.617 (.247)	.63 (.25)
Some college	.63 (.21)	.604 (.279)	.62 (.23)
HS or less	.49 (.20)	.583 (.243)	.60 (.22)
Model	p = .203, η^2 = .05	p = .836, η^2 = .002	p = .867, η^2 = .001

Note. Values are *M* (*SD*) of the proportion of science articles selected. Religion presented with 3-category (Christian / Non-religious / Other religion) and 2-category (Non-religious vs. Religious) breakdowns. *p < .05. **p < .01. ***p < .001.

Figure 22

Science Article Selection by Political Party Across All Three Experiments

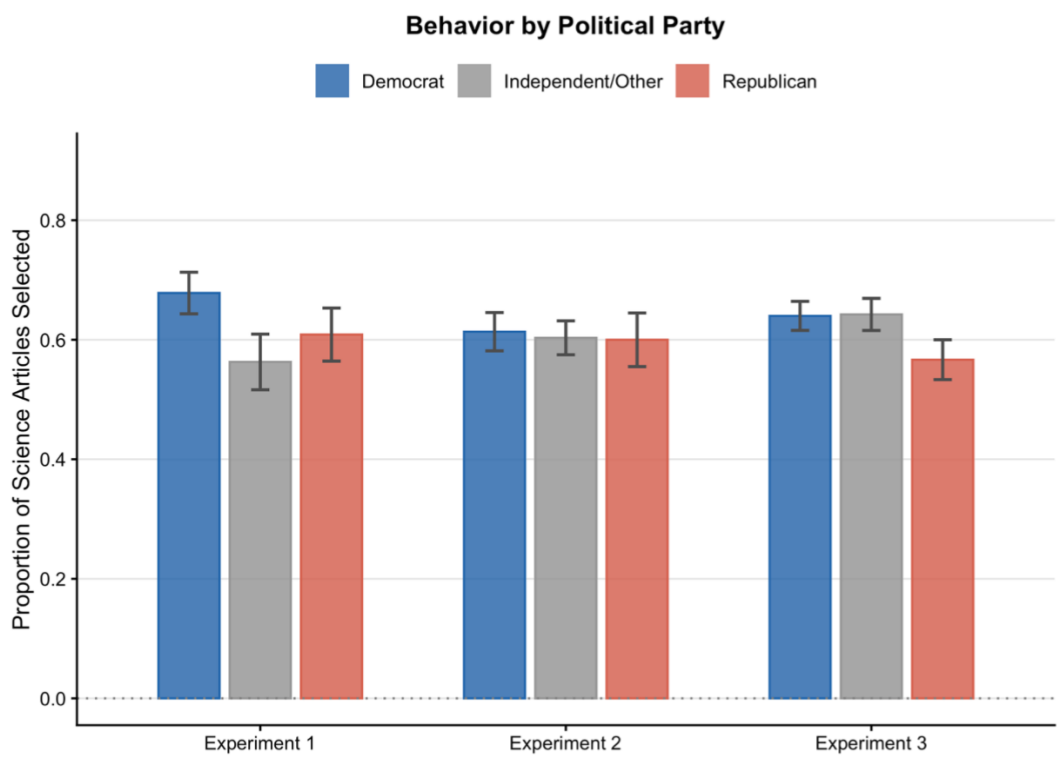


Figure 23

Science Article Selection by Political Views Across All Three Experiments

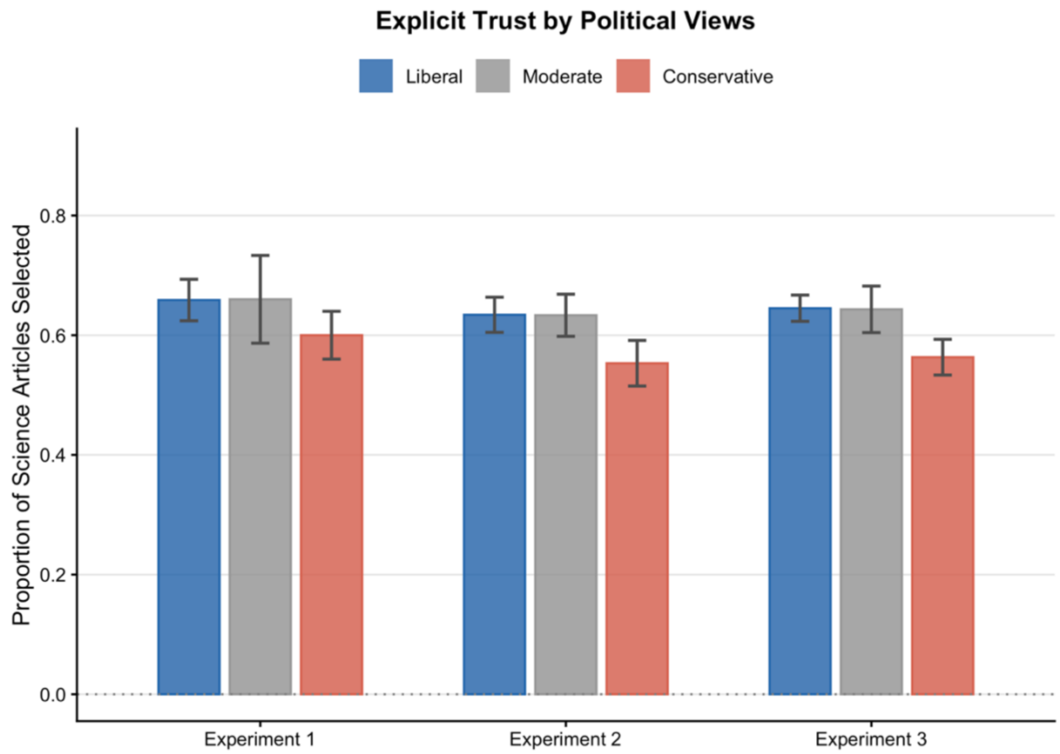


Figure 24

Science Article Selection by Three-Category Religion Across All Three Experiments

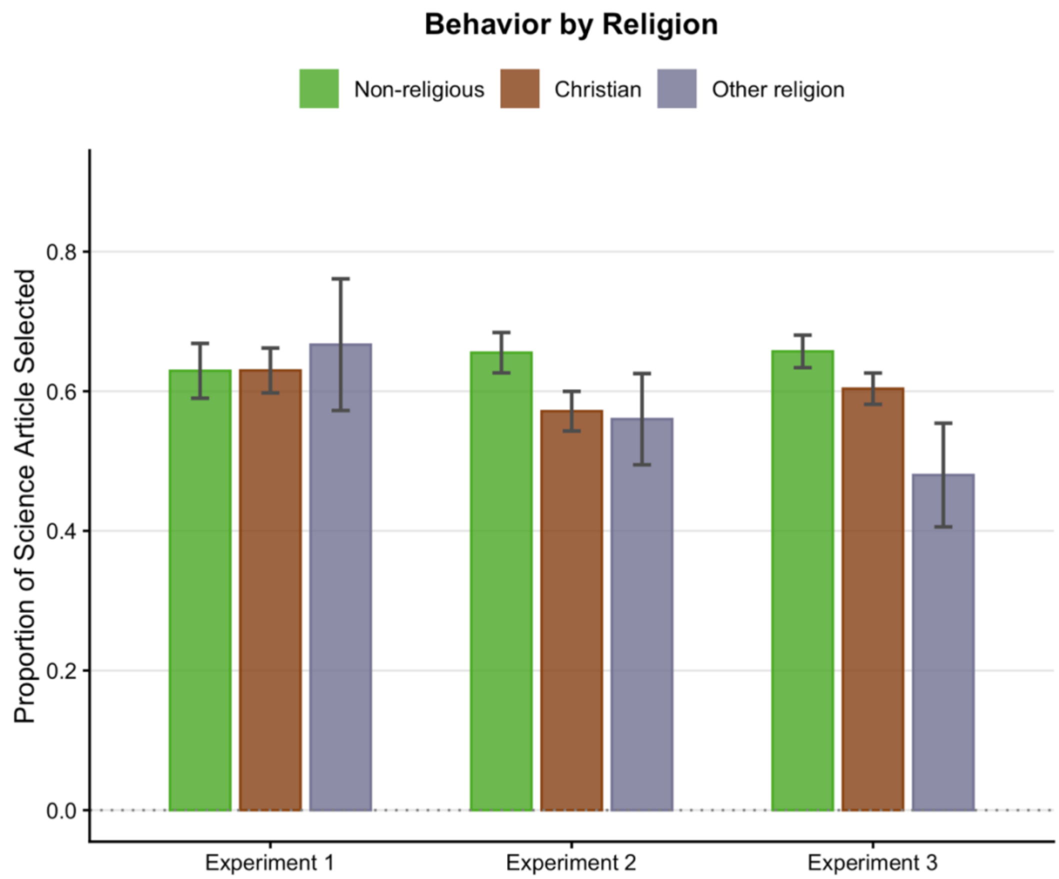
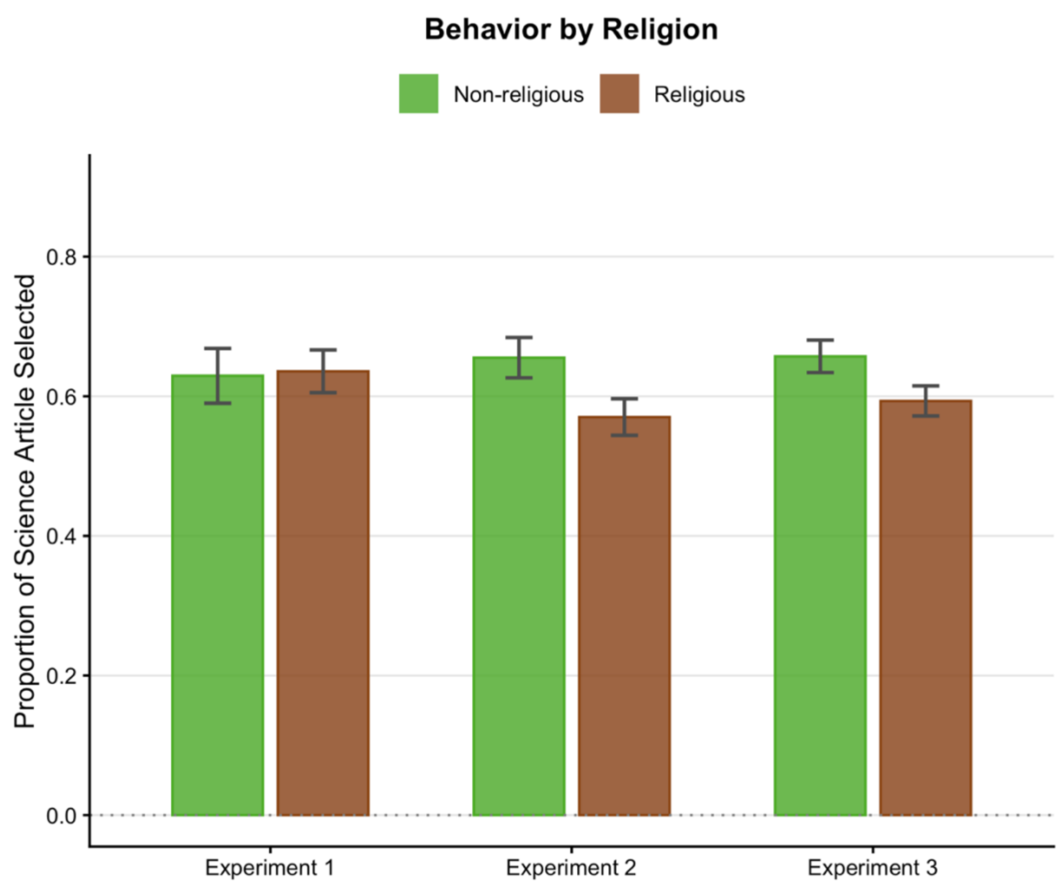


Figure 25

Science Article Selection by Two-Category Religion Across All Three Experiments



Demographic Moderators of Experimental Effects

No demographic variable significantly moderated the primary experimental effects: the trust-behavior relationship in Experiment 1, the framing effect in Experiment 2, or the framing and uncertainty effects in Experiment 3. Two findings emerged from the Experiment 1 moderation analyses, though neither involved a significant interaction term: higher education was associated with greater science article selection independently of implicit trust in science ($b = 0.04$, $p = .040$), and Independents/Others selected significantly fewer science articles than Democrats as a main effect ($b = -0.12$, $p = .042$).

In Experiment 2, a significant framing × religion interaction emerged for implicit trust in science (b = -0.57, SE = 0.22, p = .010), driven by participants in the "Other religion" category (n = 10) showing a reversed framing pattern relative to Christians. However, this finding should be interpreted with caution given the small cell size. In Experiment 3, the framing main effect on implicit trust in science remained marginally significant across demographic models (e.g., b = 0.14, p = .026 in the gender model), consistent with the primary ANOVA result, but no demographic variable interacted significantly with framing or uncertainty on any outcome.

Exploratory Implicit and Explicit Discrepancy

Although implicit and explicit measures theoretically measure people's trust in science, they assess trust in science through fundamentally different processes. Explicit measures capture consciously endorsed beliefs that are subject to deliberate reflection and motivational control, while implicit measures capture automatic evaluative associations that operate more independently of conscious intention (Nosek, 2005; Nosek, 2007). Because these two modes of evaluation are related but distinct, they do not always converge, and the *degree of misalignment* between them, also known as implicit-explicit discrepancy, can itself be a theoretically meaningful individual difference.

In the context of trust in science, discrepancy may be important because science is a domain with clear normative expectations, raising the possibility that people's automatic associations between trust and science may diverge from their deliberate, consciously reported trust. The discrepancy may happen because of motivational factors, differential history with science, or the influence of social norms and/or social context on controlled responding. With this in mind, I computed two discrepancy indices from z-scored versions of both measures across all three experiments using techniques from Windsor-Shellard and Haddock (2014) and Briñol and colleagues (2006): (1) an *absolute discrepancy* score ($|z(\text{SC-IAT}) - z(\text{explicit trust})|$), where higher values indicate greater misalignment regardless of direction; and (2) a *directional discrepancy* score ($z(\text{SC-IAT}) - z(\text{explicit trust})$), where positive values indicate implicit trust exceeding explicit trust and negative values indicate the reverse. I examined if discrepancy varied by demographic group or experimental condition, if demographic patterns in discrepancy replicated across experiments, and if discrepancy predicted science article selection.

Discrepancy by Demographic Group

A consistent pattern emerged for political orientation across all three experiments. Conservatives showed greater absolute discrepancy than liberals, indicating greater misalignment between implicit trust in science and the explicit trust composite. Pooled analyses controlling for experiment confirmed significant effects of political views, $F(2, 471) = 6.56$, $p = .002$ (see Figure 26), and political party, $F(2, 482) = 6.25$, $p = .002$ (see Figure 27). Education showed a marginal effect ($p = .059$), while religion and gender were non-significant (both ps $> .16$). See Table 25 for full results.

Table 25

Absolute Discrepancy |z(SC-IAT) - z(Explicit)| by Demographic Group Across Studies

Demographic	Exp. 1 *M (SD)*	Exp. 2 *M (SD)*	Exp. 3 *M (SD)*	Pooled *p*
Political views				
Liberal	0.81 (0.61)	0.88 (0.66)	0.96 (0.74)	
Moderate	1.23 (0.84)	0.98 (0.66)	0.93 (0.69)	
Conservative	1.14 (1.00)	1.28 (0.91)	1.14 (0.75)	.002**
Political party				
Democrat	0.76 (0.57)	0.86 (0.66)	0.97 (0.74)	
Independent/Other	1.09 (0.79)	1.14 (0.81)	0.97 (0.79)	
Republican	1.20 (1.03)	1.32 (0.82)	1.11 (0.71)	.002**
Religion				
Non-religious	0.86 (0.60)	1.06 (0.68)	0.91 (0.75)	
Religious	0.96 (0.81)	1.03 (0.82)	1.10 (0.75)	.161
Education				
HS or less	0.78 (0.60)	0.82 (0.63)	0.88 (0.75)	
Some college	0.96 (0.80)	1.20 (0.74)	1.12 (0.85)	
Bachelor's+	0.96 (0.78)	1.01 (0.79)	0.98 (0.73)	.059†
Gender				
Man	0.85 (0.71)	1.20 (0.83)	1.00 (0.79)	
Woman	1.04 (0.83)	0.90 (0.67)	1.03 (0.77)	.705

Note. Pooled F tests control for study membership. $N = 497$ total (98, 171, 228 for Studies 1-3, respectively). $^{**}p < .01$. $^{†}p < .10$.

Figure 26

Absolute Implicit-Explicit Discrepancy by Political Views

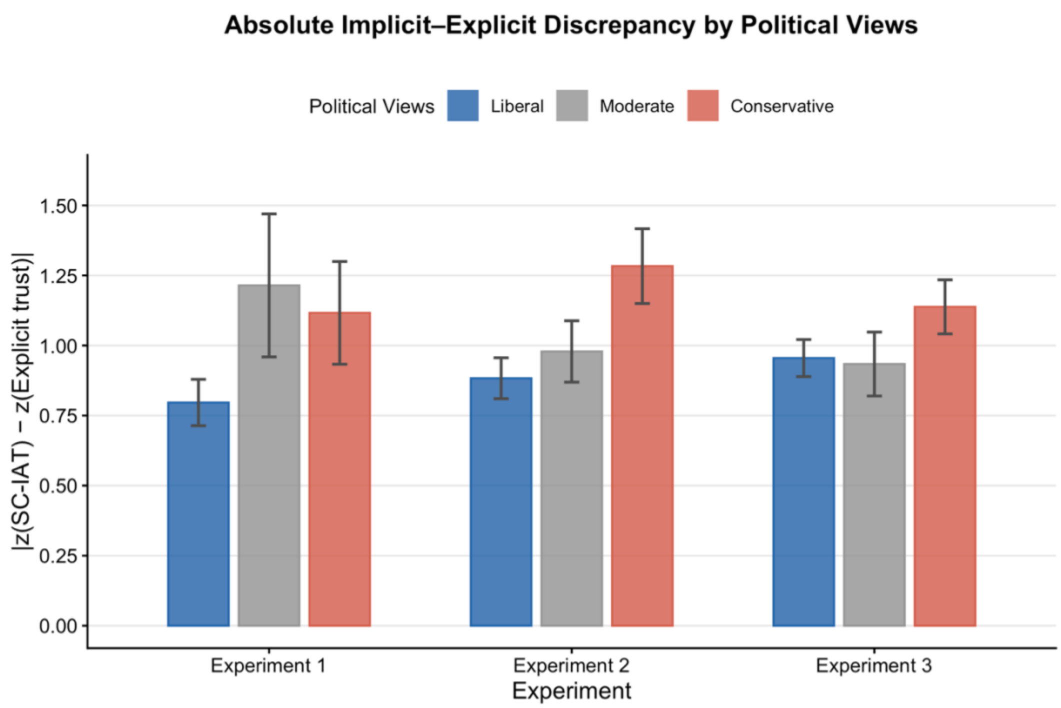
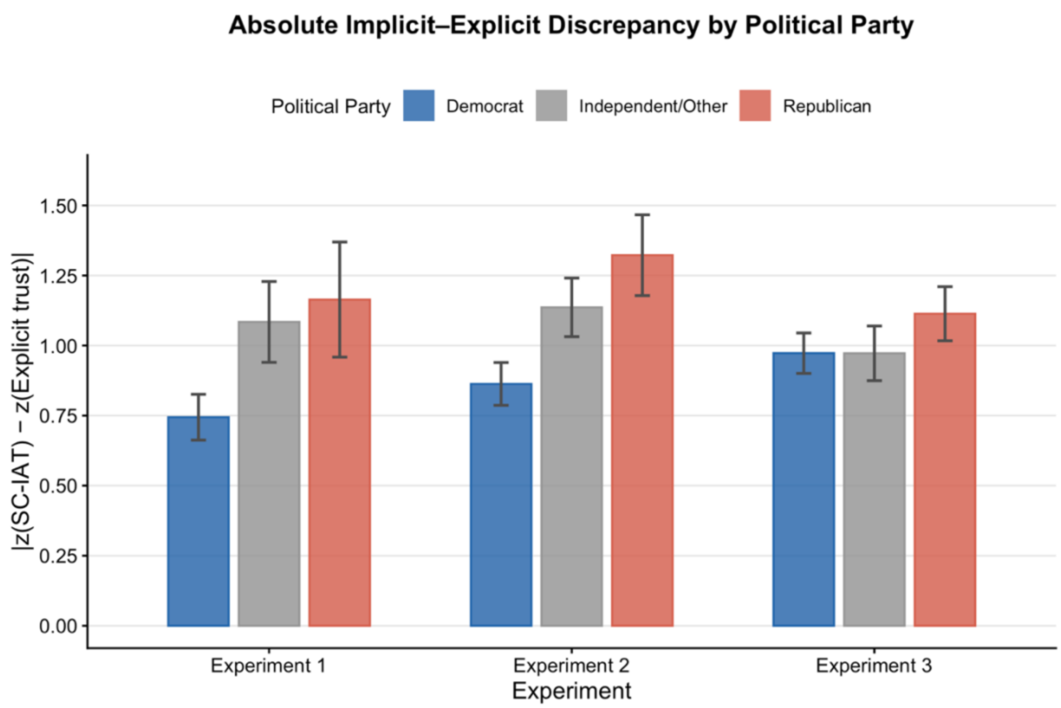


Figure 27

Absolute Implicit-Explicit Discrepancy by Political Party



A similar pattern emerged for directional discrepancy such that conservatives consistently showed positive directional discrepancy (implicit trust in science exceeding explicit trust) while liberals consistently showed negative directional discrepancy (explicit trust exceeding implicit trust in science) across all three experiments. This suggests that conservatives hold more positive implicit associations with science than they report explicitly, while liberals' explicit trust in science exceeds their implicit associations (see Figure 28). Democrats showed the smallest absolute discrepancy (M = .893 pooled), while Republicans showed the largest (M = 1.19), suggesting that political identity more strongly constrains explicit expressions of science trust among conservatives (see Figure 29). See Table 26 for full results.

Table 26

Directional Discrepancy z(SC-IAT) - z(Explicit) by Demographic Group Across Experiments

Demographic	Exp. 1 *M (SD)*	Exp. 2 *M (SD)*	Exp. 3 *M (SD)*	Pooled *p*
Political views				
Liberal	-0.36 (0.95)	-0.26 (1.08)	-0.19 (1.20)	
Moderate	0.24 (1.52)	-0.08 (1.19)	0.01 (1.17)	
Conservative	0.62 (1.40)	0.48 (1.51)	0.38 (1.31)	.001**
Political party				
Democrat	-0.26 (0.92)	-0.40 (1.01)	-0.37 (1.17)	
Independent/Other	-0.13 (1.36)	0.31 (1.37)	0.20 (1.24)	
Republican	0.70 (1.43)	0.37 (1.53)	0.37 (1.27)	< .001**
Religion				
Non-religious	-0.31 (0.99)	-0.26 (1.24)	-0.09 (1.17)	
Religious	0.18 (1.21)	0.25 (1.30)	0.02 (1.33)	.005**
Education				
HS or less	0.01 (1.08)	-0.22 (1.02)	-0.03 (1.17)	
Some college	0.24 (1.20)	-0.13 (1.41)	0.07 (1.41)	
Bachelor's+	-0.14 (1.21)	0.17 (1.27)	-0.06 (1.22)	.753
Gender				
Man	-0.04 (1.09)	0.08 (1.46)	0.04 (1.28)	
Woman	0.08 (1.29)	-0.03 (1.12)	-0.06 (1.29)	.580

Note. Positive values indicate implicit trust in science exceeding explicit trust; negative values indicate explicit trust exceeding implicit trust. Pooled F tests (or Welch's t for gender) control for experiment membership. $N = 497$ total (98, 171, 228 for Experiments 1–3, respectively). Religion coded as non-religious (atheist/agnostic/no religion) vs. religious. Gender pooled p from Welch's t-test.**$p < .01$.

Figure 28

Directional Implicit-Explicit Discrepancy by Political Views

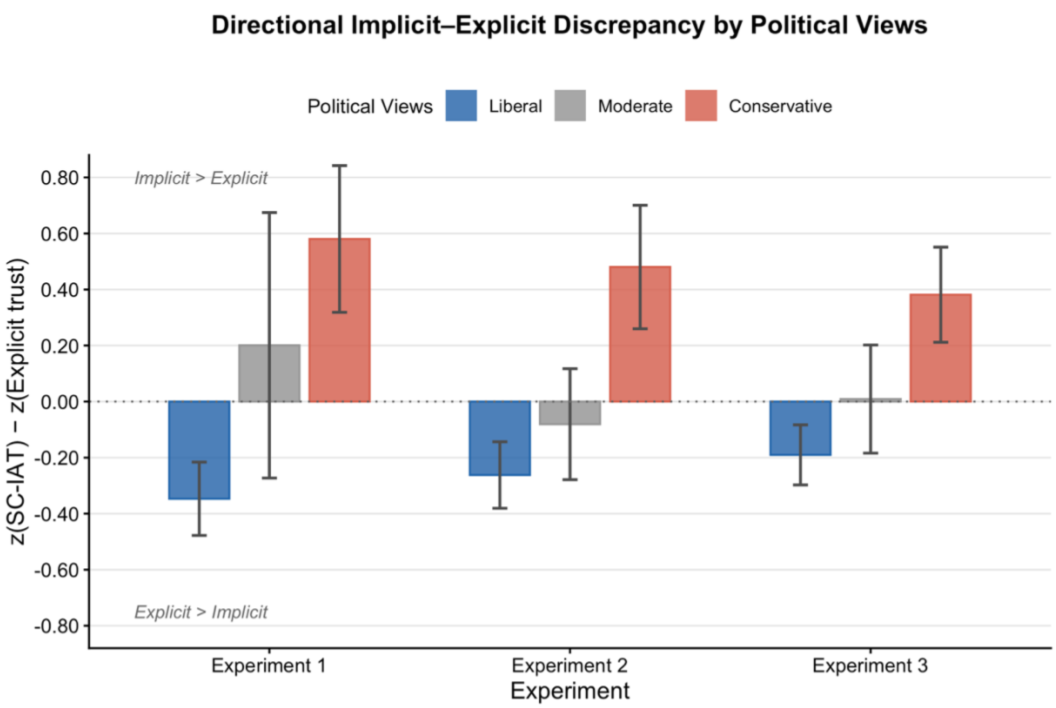
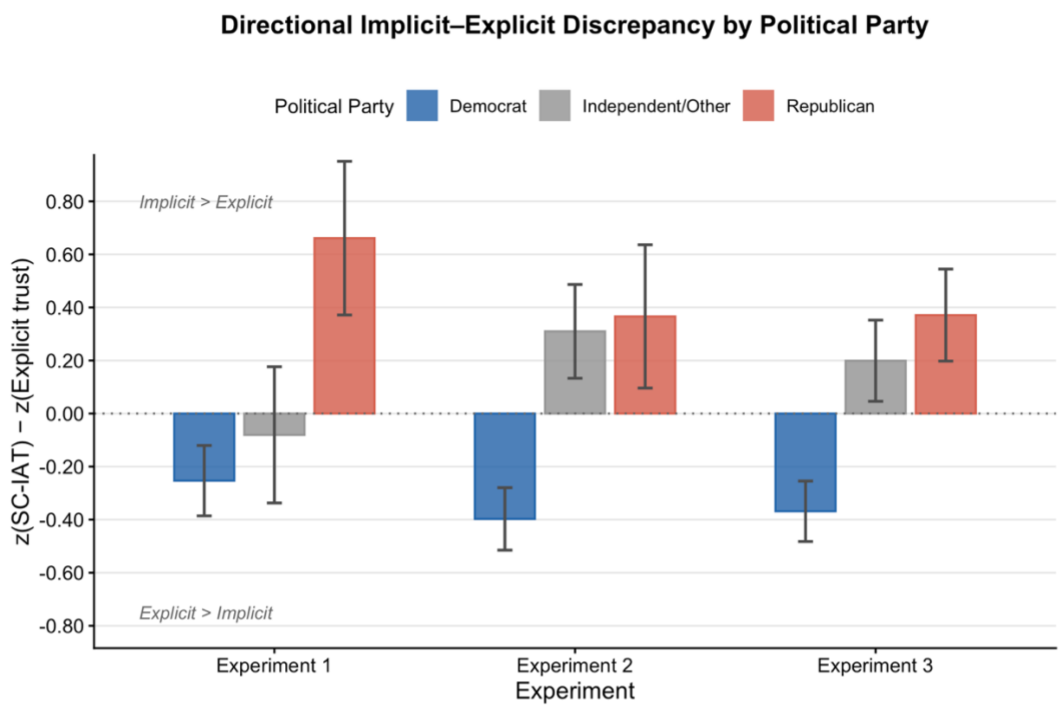


Figure 29

Directional Implicit-Explicit Discrepancy by Political Party



Discrepancy by Experimental Condition

Neither framing nor uncertainty significantly affected absolute discrepancy in Experiments 2 or 3. In Experiment 2, discrepancy did not differ between static and dynamic framing conditions, $t(169) = 0.76$, $p = .452$. In Experiment 3, framing ($p = .886$) and uncertainty ($p = .135$) both produced non-significant differences, and their interaction was non-significant, $F(1, 224) = 0.02$, $p = .886$. These results suggest that the framing and uncertainty manipulations shifted the level of implicit trust in science (as shown in the primary analyses) without altering the gap between implicit and explicit trust; the size and direction of the implicit-explicit discrepancy appear to be determined by stable characteristics rather than immediate contextual framing. See Table 27.

Table 27

Implicit-Explicit Discrepancy by Experimental Condition (Studies 2 and 3)

Condition	Abs *M (SD)*	Dir *M (SD)*	*n*	*t* or *F* (*p*)
Experiment 2: Framing condition				
Static	1.10 (0.81)	0.09 (1.37)	85	
Dynamic	1.01 (0.76)	-0.09 (1.27)	86	$t = 0.76$, $p = .452$
Experiment 3: Framing condition				
Static	1.03 (0.75)	-0.20 (1.26)	107	
Dynamic	1.01 (0.80)	0.18 (1.28)	121	$t = 0.14$, $p = .886$
Experiment 3: Uncertainty condition				
Low uncertainty	0.94 (0.74)	-0.03 (1.20)	119	
High uncertainty	1.10 (0.80)	0.03 (1.36)	109	$t = -1.50$, $p = .135$
Experiment 3: Framing × Uncertainty (2×2 ANOVA)				
Static / Low uncertainty	0.96 (0.72)	-0.32 (1.28)	59	
Static / High uncertainty	1.10 (0.79)	-0.06 (1.29)	48	
Dynamic / Low uncertainty	0.93 (0.78)	0.26 (1.21)	60	
Dynamic / High uncertainty	1.10 (0.82)	0.10 (1.36)	61	$F = 0.02$, $p = .886$

Note. Abs = absolute discrepancy; Dir = directional discrepancy. *t*-tests are two-tailed. The 2×2 ANOVA tests framing × uncertainty on absolute discrepancy.

Discrepancy Predicting Science Article Selection

To test whether the degree of implicit-explicit alignment predicted science article selection beyond what each measure contributed individually, I regressed *z*-scored science article selection on absolute and directional discrepancy indices across three models: (M1) absolute discrepancy alone, (M2) absolute discrepancy controlling for both *z*-scored trust measures, and (M3) directional discrepancy alone. I did not enter directional discrepancy alongside both trust measures due to perfect collinearity, as directional discrepancy is a linear combination of the two measures.

In Experiment 1, absolute discrepancy significantly predicted science article selection above and beyond both trust measures ($\beta = 0.33$, $p = .014$), indicating that greater misalignment between implicit trust in science and the explicit trust composite was associated with more science article selection, independent of the direction or level of either measure. Directional discrepancy was also significant alone ($\beta = -0.21$, $p = .010$), with participants whose implicit trust in science exceeded their explicit trust selecting fewer science articles. In Experiment 2, neither absolute nor directional discrepancy significantly predicted science article selection (all ps > .09). Experiment 3 replicated the directional discrepancy effect from Experiment 1 ($\beta = -0.12$, $p = .022$), while absolute discrepancy was non-significant. The directional discrepancy effect was consistent in direction across Experiments 1 and 3: participants whose implicit trust in science exceeded their explicit trust selected fewer science articles in both experiments (see Figure 30). See Table 28 and 29.

Table 28

Implicit-Explicit Discrepancy Predicting Science Article Selection Across Studies

Predictor	*B (SE)*	*t*	*p*	Model fit
Experiment 1 (N = 98)				
M1: Absolute discrepancy (alone)	0.18 (.10)	1.75	.083†	$R^2 = .03$
M2: Absolute discrepancy + both trust measures	0.33 (.13)	2.50	.014*	$R^2 = .13$
M3: Directional discrepancy (alone)	-0.21 (.08)	-2.64	.010**	$R^2 = .07$
Experiment 2 (N = 171)				
M1: Absolute discrepancy (alone)	-0.16 (.10)	-1.68	.094†	$R^2 = .02$
M2: Absolute discrepancy + both trust measures	-0.09 (.10)	-0.83	.408	$R^2 = .05$
M3: Directional discrepancy (alone)	-0.02 (.06)	-0.41	.680	$R^2 = .001$
Experiment 3 (N = 228)				
M1: Absolute discrepancy (alone)	-0.03 (.09)	-0.37	.713	$R^2 = .001$
M2: Absolute discrepancy + both trust measures	0.01 (.09)	0.11	.913	$R^2 = .03$
M3: Directional discrepancy (alone)	-0.12 (.05)	-2.31	.022*	$R^2 = .02$

Note. All models use z-scored science article selection as the dependent variable.

**p* < .05. ***p* < .01. †*p* < .10.

Table 29

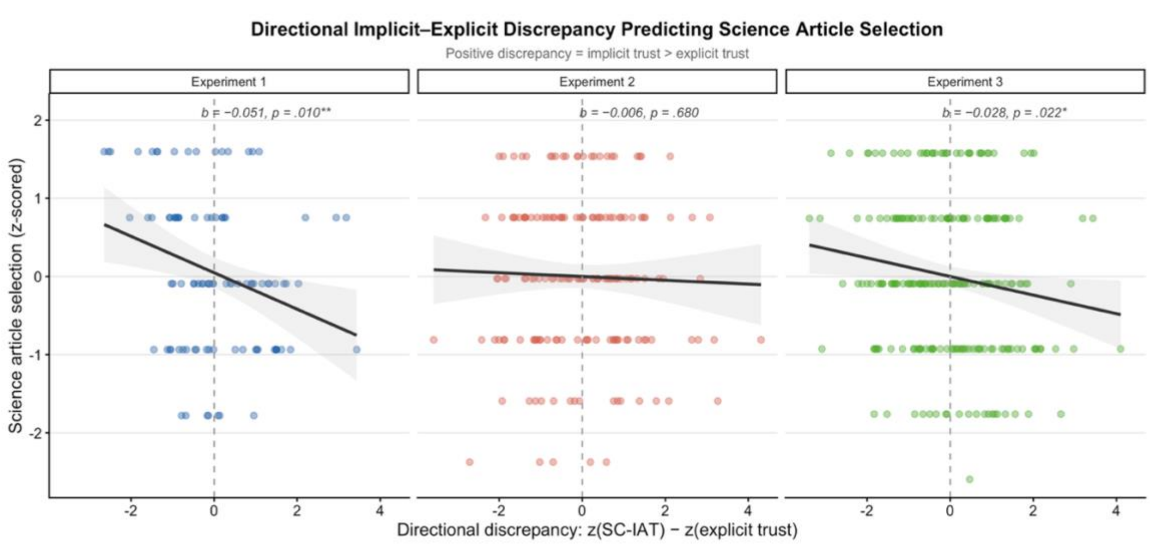
Cross-Experiment Summary: Directional Discrepancy Predicting Science Article Selection

Experiment	*N*	*B (SE)*	*p*	R^2
Experiment 1	98	-0.21 (.08)	.010**	.07
Experiment 2	171	-0.02 (.06)	.680	.001
Experiment 3	228	-0.12 (.05)	.022*	.02

Note. β from simple regression of z-scored behavior on directional discrepancy (*z*(SC-IAT) - *z*(explicit trust)). Negative β indicates that participants with implicit trust exceeding explicit trust select fewer science articles. *$p < .05$. **$p < .01$.

Figure 30

Directional Discrepancy Predicting Science Article Selection Across Experiments



Mini Meta-Analysis

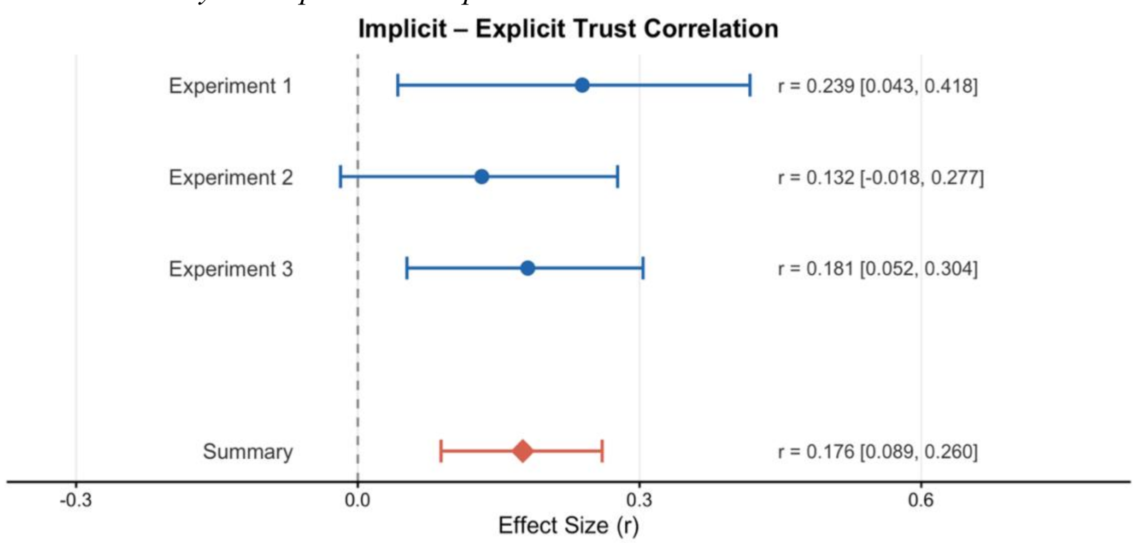
I conducted a mini meta-analysis synthesizing effect sizes across Experiments 1, 2, and 3 following the method described by Goh et al. (2016). I converted each effect size to Pearson r, Fisher r-to-z transformed, weighted by (n - 3), and back-transformed to produce a weighted mean r with 95% confidence interval. I also assessed heterogeneity using the Q statistic and I^2.

Implicit Trust in Science-Explicit Trust Correlation

Across all three experiments, implicit trust in science showed a small but consistent positive correlation with the explicit trust composite (Experiment 1: $r = .24$; Experiment 2: $r = .13$; Experiment 3: $r = .18$). The weighted mean effect was $r = .18$, $p < .001$, with no evidence of heterogeneity ($I^2 = 0.0\%$) (see Figure 31). This effect falls within the .10-.30 range reported in the broader implicit-explicit attitude literature (Hofmann et al., 2005), supporting the interpretation that the SC-IAT and explicit measures capture related but non-redundant aspects of science trust.

Figure 31

Mini Meta-Analysis: Implicit and Explicit Trust in Science Correlation



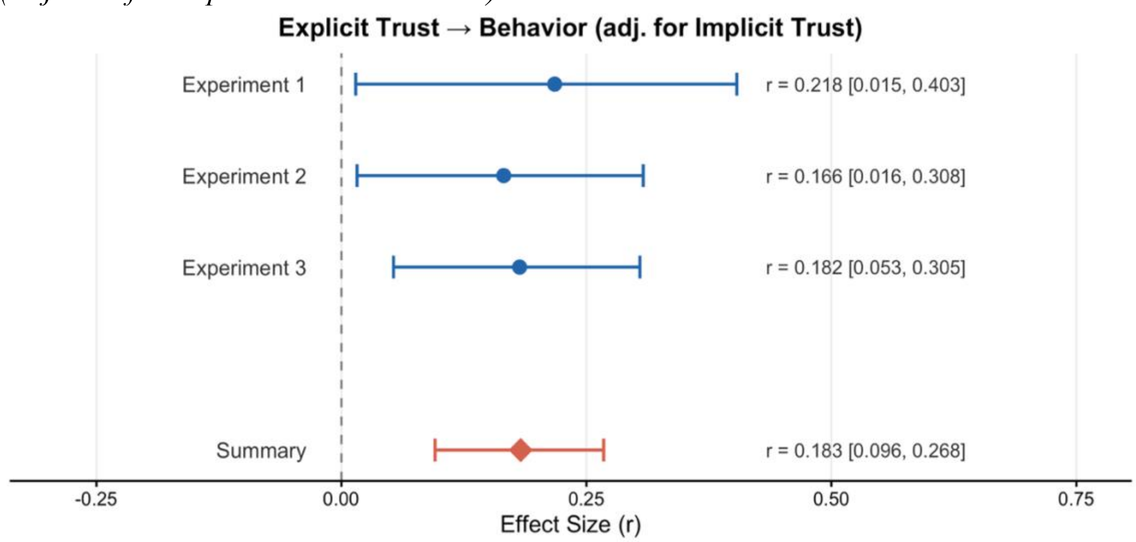
Note. r = Pearson correlation. Positive values indicate higher implicit scores associated with higher explicit scores. The diamond represents the weighted mean effect; horizontal lines are 95% confidence intervals.

Implicit and Explicit Trust Predicting Science Article Selection

The explicit trust composite showed a consistent positive association with science article selection across all three experiments (Experiment 1: $r = .22$; Experiment 2: $r = .17$; Experiment 3: $r = .18$), yielding a weighted mean of $r = .18$, $p < .001$, $I^2 = 0.0\%$ (see Figure 32). All three experiment-level confidence intervals exclude zero, and the I^2 of 0% indicates near-perfect homogeneity. The explicit trust composite is a reliable, medium-sized predictor of science article selection across experiment contexts.

Figure 32

Mini Meta-Analysis: Explicit Trust in Science Predicting Scientific Article Selection (Adjusted for Implicit Trust in Science)

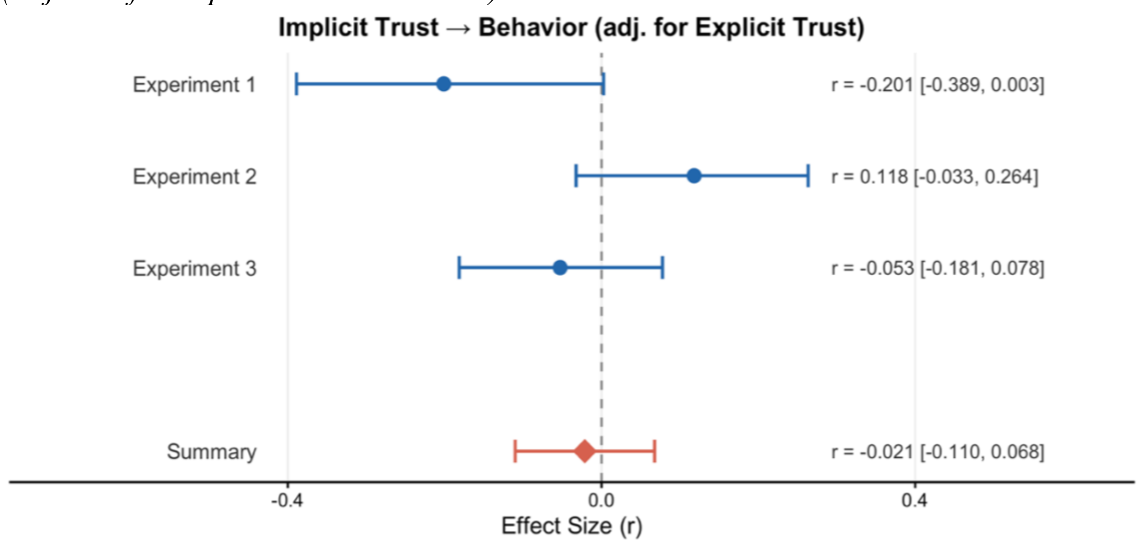


Note. r = Pearson correlation. Positive values indicate higher explicit trust associated with more science articles selected. The diamond represents the weighted mean effect; horizontal lines are 95% confidence intervals.

In contrast, implicit trust in science showed no consistent relationship with science article selection when controlling for the explicit trust composite. The weighted mean was $r = -.02$, $p = .640$, and heterogeneity was high ($I^2 = 76.1\%$) (see Figure 33). This heterogeneity is substantively meaningful: Experiment 1 showed a significant negative effect (r = -.20), Experiment 3 a small negative effect (r = -.05), and Experiment 2 a small positive effect (r = .12). The relationship between implicit trust in science and science article selection is thus inconsistent across experiments, in contrast to the explicit trust composite. This asymmetry should be explored in future research.

Figure 33

Mini Meta-Analysis: Implicit Trust in Science Predicting Scientific Article Selection (Adjusted for Explicit Trust in Science)



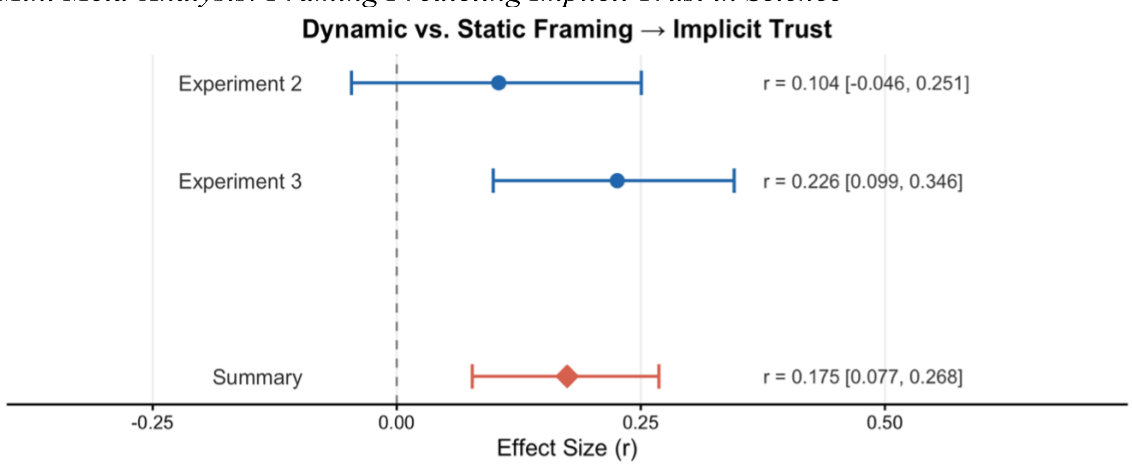
Note. r = Pearson correlation. Positive values indicate higher explicit trust associated with more science articles selected, negative values indicate higher implicit trust associated with fewer science articles selected. The diamond represents the weighted mean effect; horizontal lines are 95% confidence intervals.

Effect of Framing on Implicit Trust in Science, Explicit Trust, and Behavior

Dynamic framing consistently increased implicit trust in science relative to static framing across both experimental studies (r = .10 in Experiment 2; r = .23 in Experiment 3), yielding a weighted summary of r = .18, p < .001 (see Figure 34). Heterogeneity was modest (I^2 = 33.4%), and the effect is larger in Experiment 3. Framing also affected the explicit trust composite in the same direction, but with substantially more variability between experiments (r = .20 in Experiment 2 vs. r = .03 in Experiment 3), yielding a weighted mean of r = .10, p = .040, I^2 = 61.8% (see Figure 35). This high heterogeneity reflects the fact that the framing effect on explicit trust was significant in Experiment 2 but not Experiment 3. Framing had no meaningful effect on science article selection (r = .04, p = .389, I^2 = 0.0%) (see Figure 36). Together, these results suggest that framing shifts implicit and explicit trust in science without translating into immediate behavioral change.

Figure 34

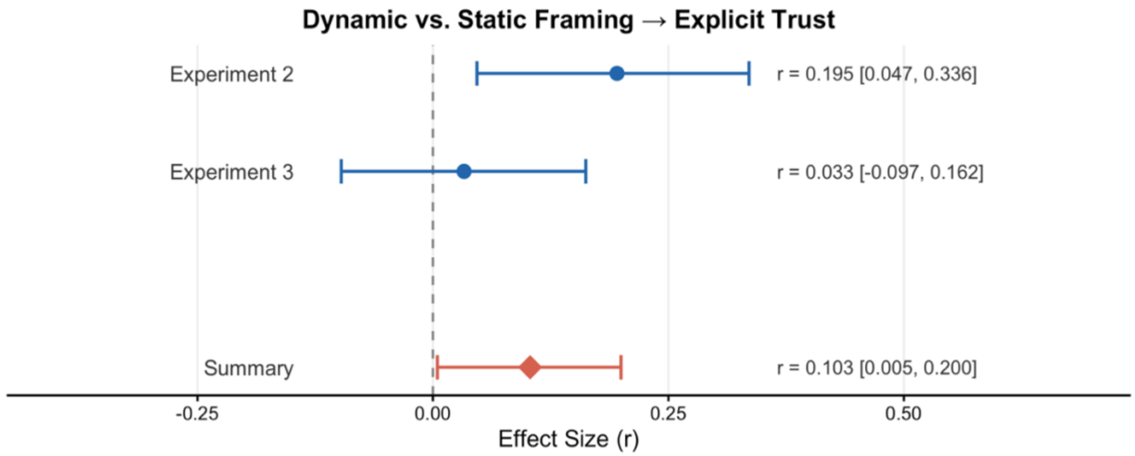
Mini Meta-Analysis: Framing Predicting Implicit Trust in Science



Note. R estimated from ANOVA F-statistic and reflects magnitude of group differences only. The diamond represents the weighted mean effect; horizontal lines are 95% confidence intervals.

Figure 35

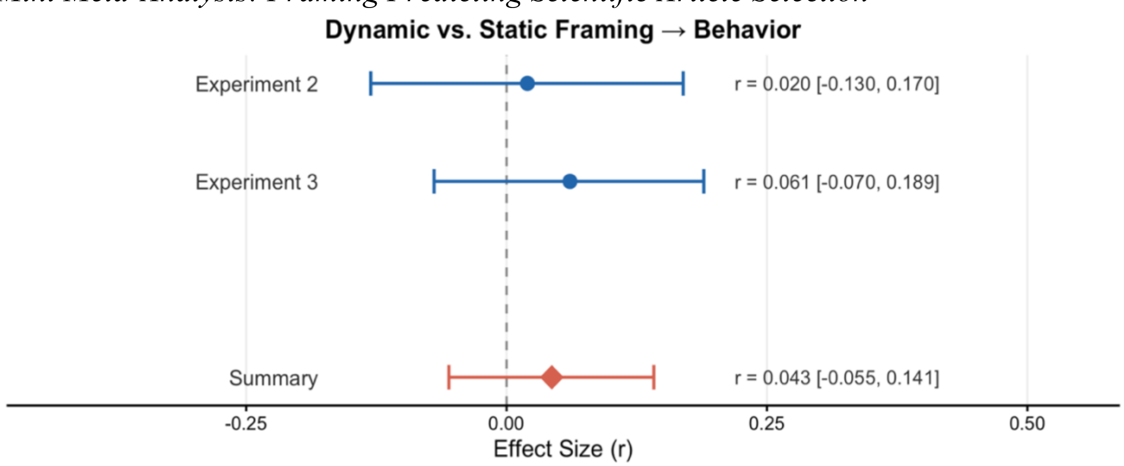
Mini Meta-Analysis: Framing Predicting Explicit Trust in Science



Note. r estimated from ANOVA F-statistic and reflects magnitude of group differences only. The diamond represents the weighted mean effect; horizontal lines are 95% confidence intervals.

Figure 36

Mini Meta-Analysis: Framing Predicting Scientific Article Selection



Note. r estimated from ANOVA F-statistic and reflects magnitude of group differences only. The diamond represents the weighted mean effect; horizontal lines are 95% confidence intervals.

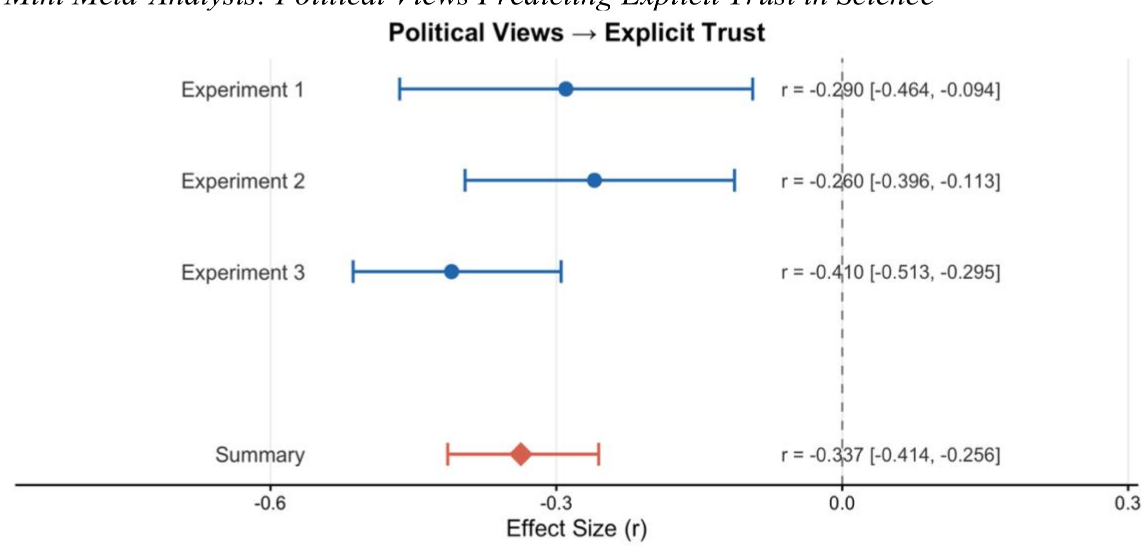
Demographic Predictors of Explicit Trust in Science

Political orientation showed the largest and most consistent demographic effects on the explicit trust composite; political views (liberal-conservative) yielded $r = -.34$, $p <$

.001, $I^2 = 34.0\%$ (see Figure 37), and political party yielded $r = .38$, $p < .001$, $I^2 = 0.0\%$ (see Figure 38). Both effects are large, significant, and have relatively low homogeneity across all three experiments. Conservatives and Republicans reported substantially lower explicit trust in science than liberals and Democrats in every sample. Political interest showed a medium and consistent effect ($r = .22$, $I^2 = 0.0\%$; see Figure 39) such that higher political engagement was associated with greater explicit trust in science across all three experiments. Religion also predicted the explicit trust composite ($r = .24$, $p < .001$), with non-religious participants showing higher explicit trust than religious participants, and the effect was slightly larger in Experiments 1 and 2 (rs = .36, .27) than in Experiment 3 ($r = .17$), producing modest heterogeneity ($I^2 = 29.7\%$; see Figure 40). Education did not predict the explicit trust composite ($r = .03$, $p = .470$, $I^2 = 66.3\%$; see Figure 41).

Figure 37

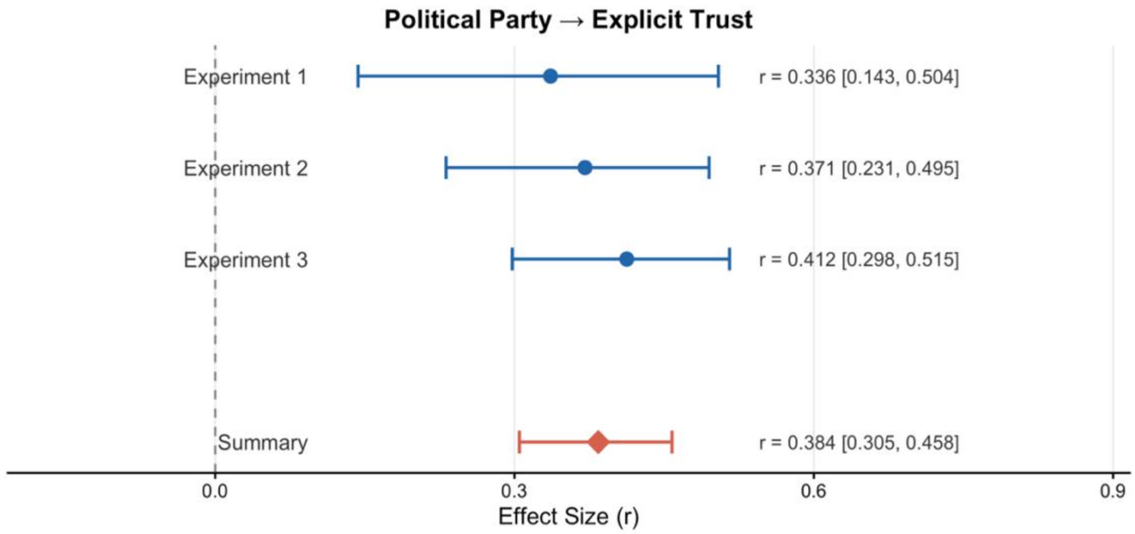
Mini Meta-Analysis: Political Views Predicting Explicit Trust in Science



Note. r = Pearson correlation. Negative values indicate higher conservatism associated with lower explicit trust in science. The diamond represents the weighted mean effect; horizontal lines are 95% confidence intervals.

Figure 38

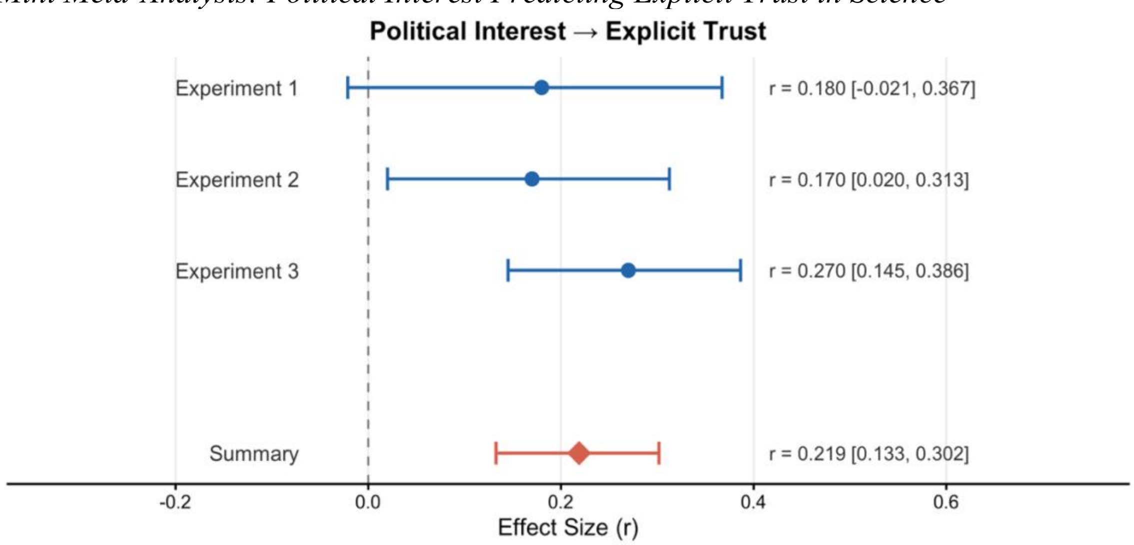
Mini Meta-Analysis: Political Party Predicting Explicit Trust in Science



Note. r estimated from ANOVA F-statistic and reflects magnitude of group differences only. The diamond represents the weighted mean effect; horizontal lines are 95% confidence intervals.

Figure 39

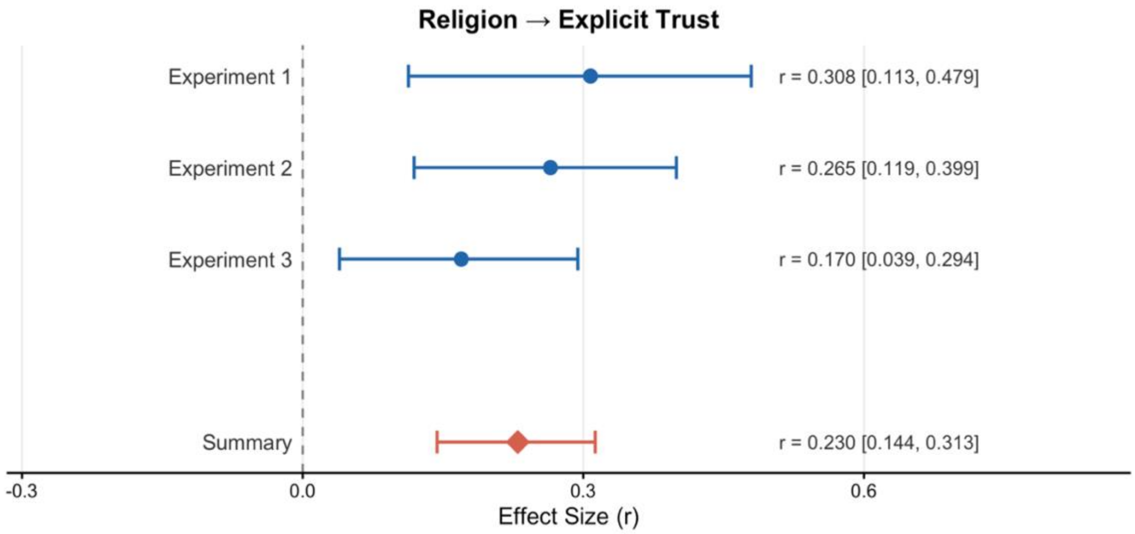
Mini Meta-Analysis: Political Interest Predicting Explicit Trust in Science



Note. r = Pearson correlation. Positive values indicate higher political interest associated with higher explicit trust in science. The diamond represents the weighted mean effect; horizontal lines are 95% confidence intervals.

Figure 40

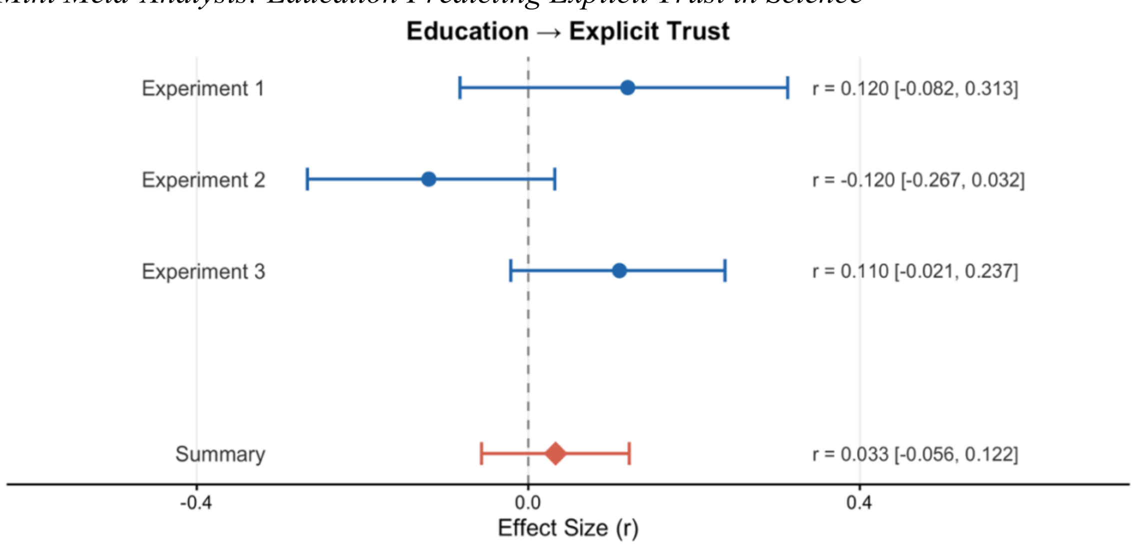
Mini Meta-Analysis: Religion Predicting Explicit Trust in Science



Note. r estimated from ANOVA F-statistic and reflects magnitude of group differences only. The diamond represents the weighted mean effect; horizontal lines are 95% confidence intervals.

Figure 41

Mini Meta-Analysis: Education Predicting Explicit Trust in Science

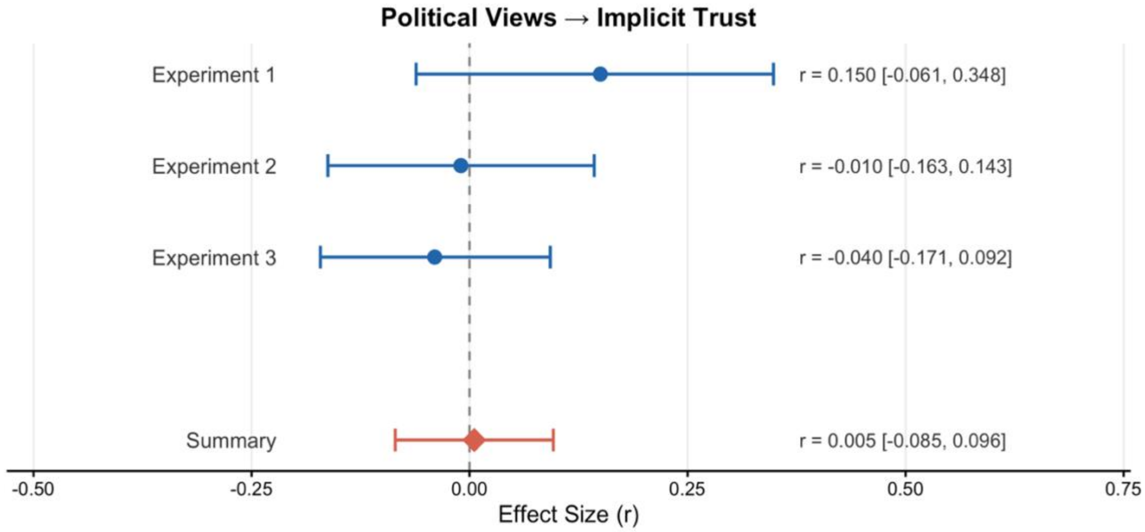


Note. r = Pearson correlation. Positive values indicate more education associated with higher explicit trust in science, negative values indicate more education associated with lower explicit trust in science. The diamond represents the weighted mean effect; horizontal lines are 95% confidence intervals.

Demographic Predictors of Implicit Trust in Science

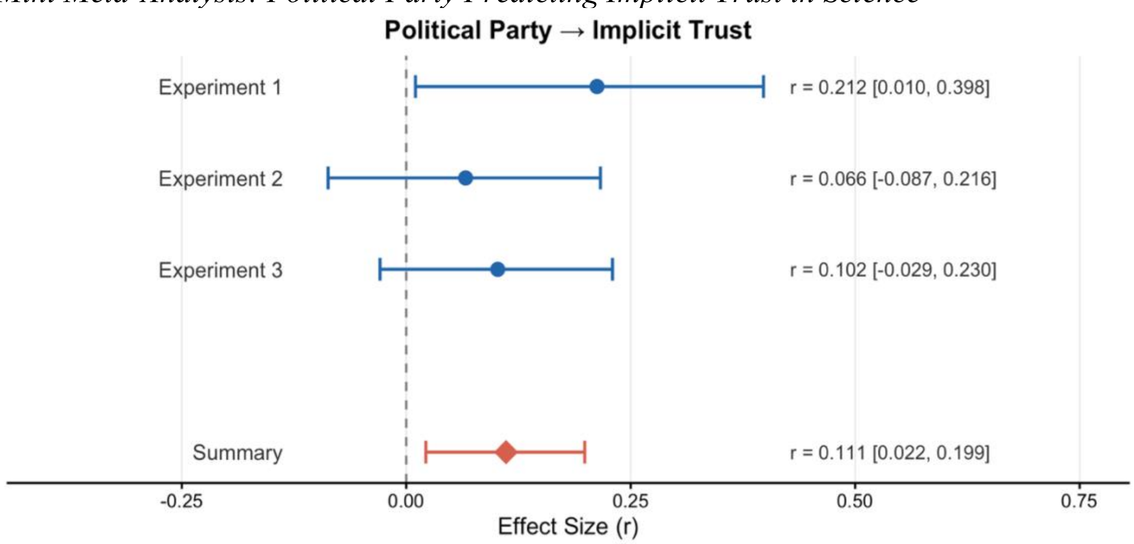
Political views did not predict implicit trust in science (r = .01, p = .908, I^2 = 12.8%; see Figure 42), however, political party did predict implicit trust in science (r = .11, p = .015, I^2 = 0.0%; see Figure 43). The political party effect was not significant in any individual experiment due to limited power but emerged clearly in the meta-analytic synthesis. Political interest showed the strongest relationship with implicit trust in science (r = .16, p < .001, I^2 = 0.0%; see Figure 44), nearly as large as the corresponding explicit trust effect. Religion did not predict implicit trust in science (r = .05, p = .243, I^2 = 0.0%; see Figure 45), however, education did have a small relationship with implicit trust in science (r = .10, p = .035, I^2 = 0.0%; see Figure 46). The presence of small but consistent political and interest-based associations with implicit trust in science suggests that the SC-IAT is not entirely independent of political identity, though the effects are substantially smaller compared to for explicit trust in science.

Figure 42
Mini Meta-Analysis: Political Views Predicting Implicit Trust in Science



Note. r = Pearson correlation. Positive values indicate higher conservatism associated with higher implicit trust in science, negative values indicate higher conservatism associated with lower implicit trust in science. The diamond represents the weighted mean effect; horizontal lines are 95% confidence intervals.

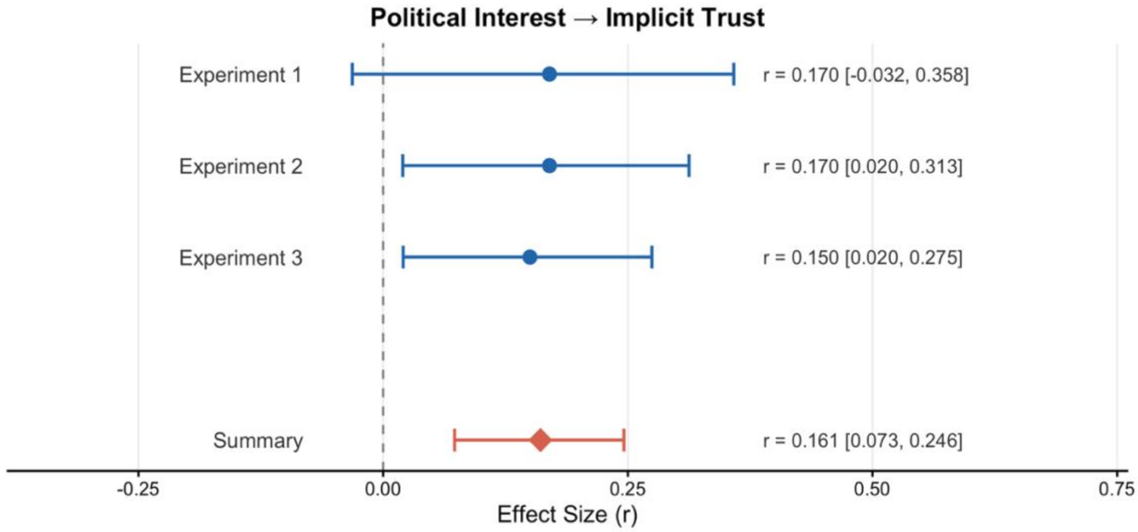
Figure 43
Mini Meta-Analysis: Political Party Predicting Implicit Trust in Science



Note. r estimated from ANOVA F-statistic and reflects magnitude of group differences only. The diamond represents the weighted mean effect; horizontal lines are 95% confidence intervals.

Figure 44

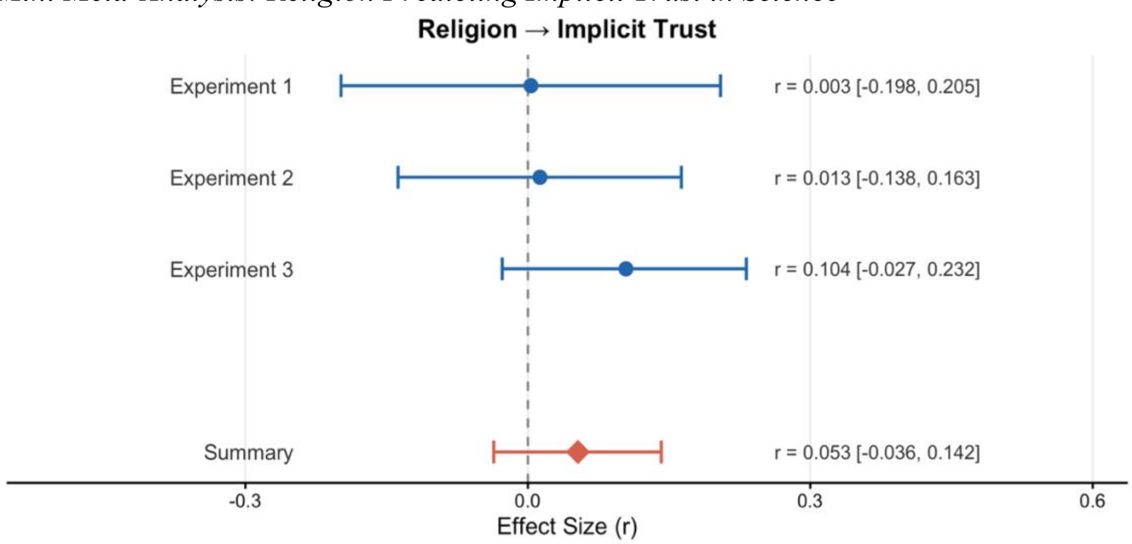
Mini Meta-Analysis: Political Interest Predicting Implicit Trust in Science



Note. r = Pearson correlation. Positive values indicate higher political interest associated with higher implicit trust in science. The diamond represents the weighted mean effect; horizontal lines are 95% confidence intervals.

Figure 45

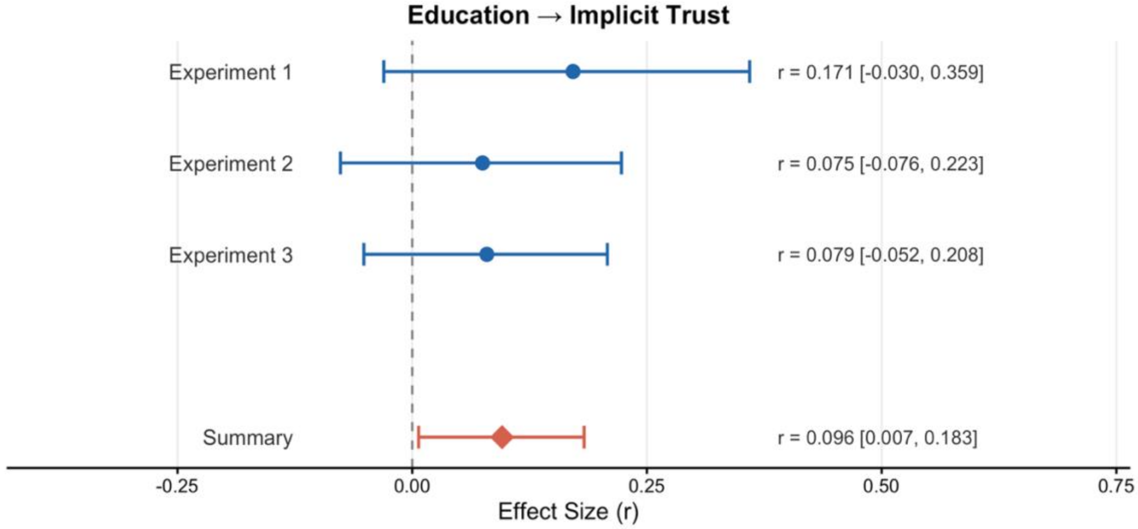
Mini Meta-Analysis: Religion Predicting Implicit Trust in Science



Note. r estimated from ANOVA F-statistic and reflects magnitude of group differences only. The diamond represents the weighted mean effect; horizontal lines are 95% confidence intervals.

Figure 46

Mini Meta-Analysis: Education Predicting Implicit Trust in Science



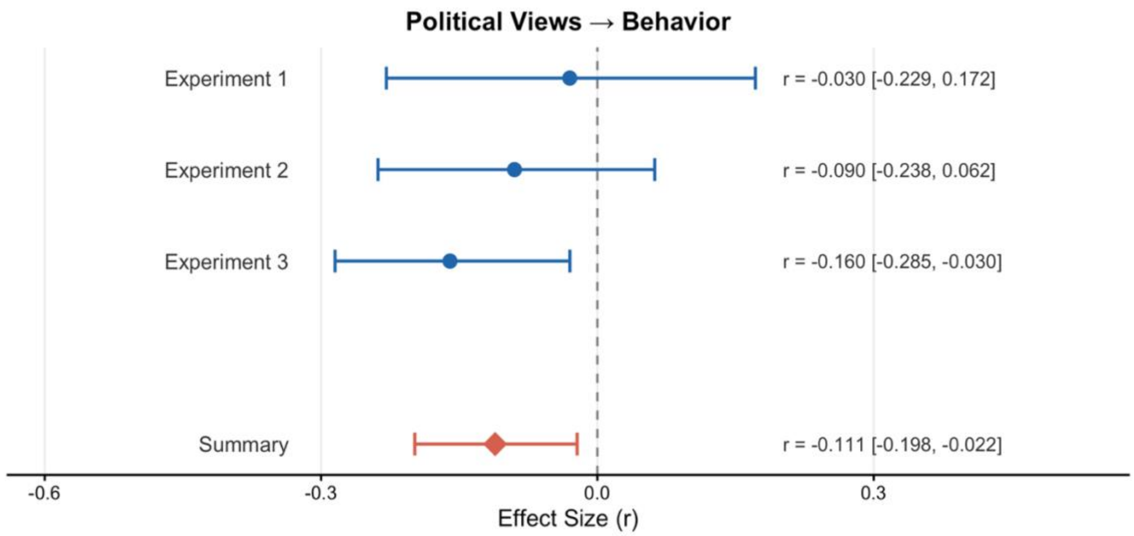
Note. r = Pearson correlation. Positive values indicate more education associated with higher implicit trust in science. The diamond represents the weighted mean effect; horizontal lines are 95% confidence intervals.

Demographics Predictors of News Article Selection Behavior

Political orientation also showed a consistent effect on article selection behavior. Political views (r = -.11, p = .015, I^2 = 0.0%; see Figure 47) and political party (r = .11, p = .020, I^2 = 0.0%; see Figure 48) both had small but consistent effects in predicting article selection behavior; conservative and Republican participants selected fewer scientific articles compared to liberals and Democrats. Similar to implicit trust in science, the effects did not emerge in any single experiment but consistently emerged in the meta-analysis. In addition, political interest (r = .15, p = .001, I^2 = 0.0%; see Figure 49) also showed a consistent significant effect such that more politically engaged participants selected more scientific articles. Religion also had a consistent effect (r = .15, p = .001, I^2 = 0.0%; see Figure 50), with non-religious participants selecting more scientific articles compared to religious participants. Education did not predict science article selection (*r* = .07, p = .133, I^2 = 0.0%; see Figure 51). The presence of small but consistent political and interest-based associations with science article selection suggests that the science article selection is also not independent of political identity and religion, though again, the effects are substantially smaller compared to explicit trust in science.

Figure 47

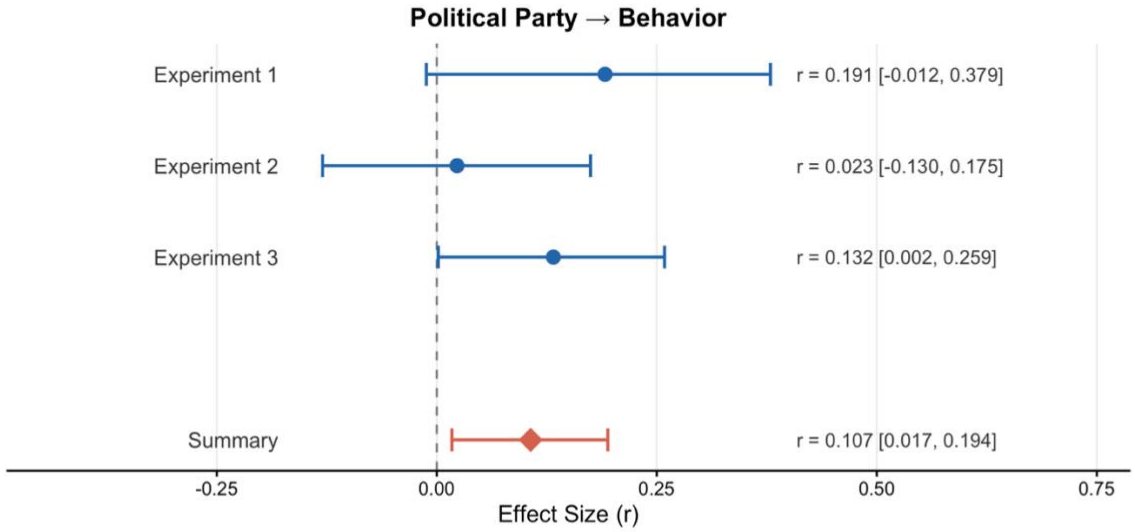
Mini Meta-Analysis: Political Views Predicting Scientific Article Selection



Note. r = Pearson correlation. Positive values indicate higher conservatism associated with more science articles selected, negative values indicate higher conservatism associated with fewer science articles selected. The diamond represents the weighted mean effect; horizontal lines are 95% confidence intervals.

Figure 48

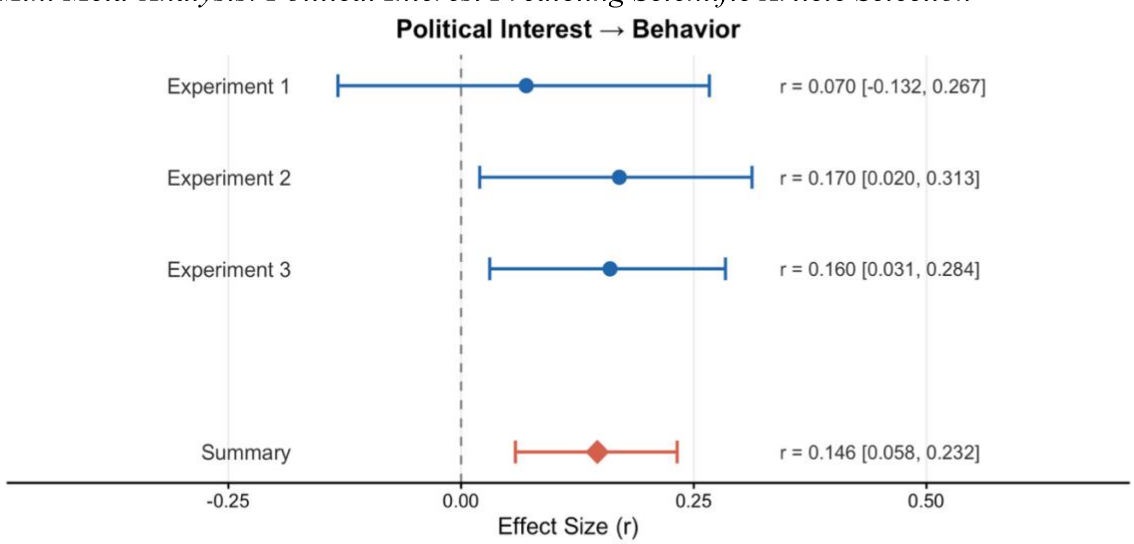
Mini Meta-Analysis: Political Party Predicting Scientific Article Selection



Note. r estimated from ANOVA F-statistic and reflects magnitude of group differences only. The diamond represents the weighted mean effect; horizontal lines are 95% confidence intervals.

Figure 49

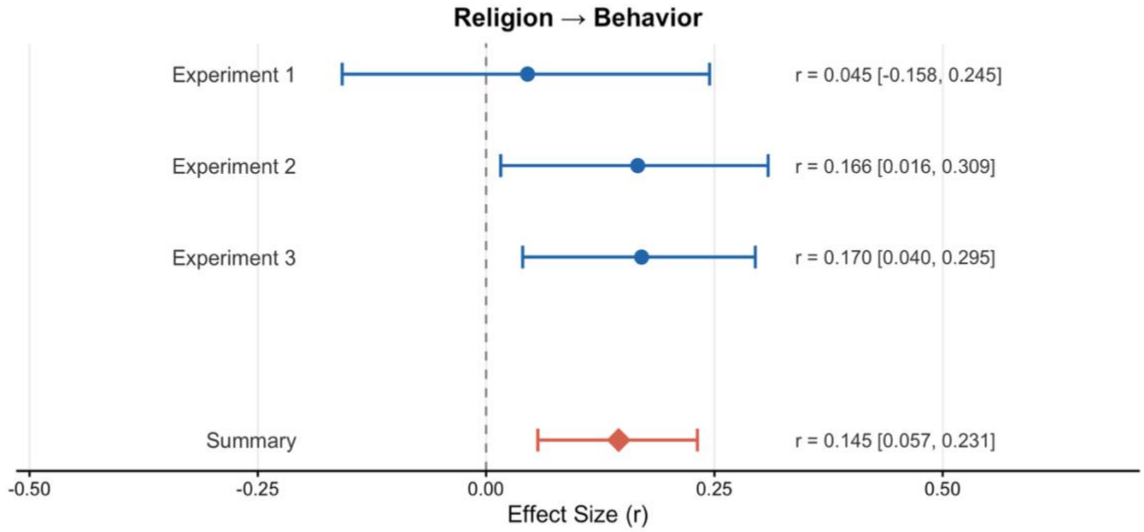
Mini Meta-Analysis: Political Interest Predicting Scientific Article Selection



Note. r = Pearson correlation. Positive values indicate higher political interest associated with more science articles selected. The diamond represents the weighted mean effect; horizontal lines are 95% confidence intervals.

Figure 50

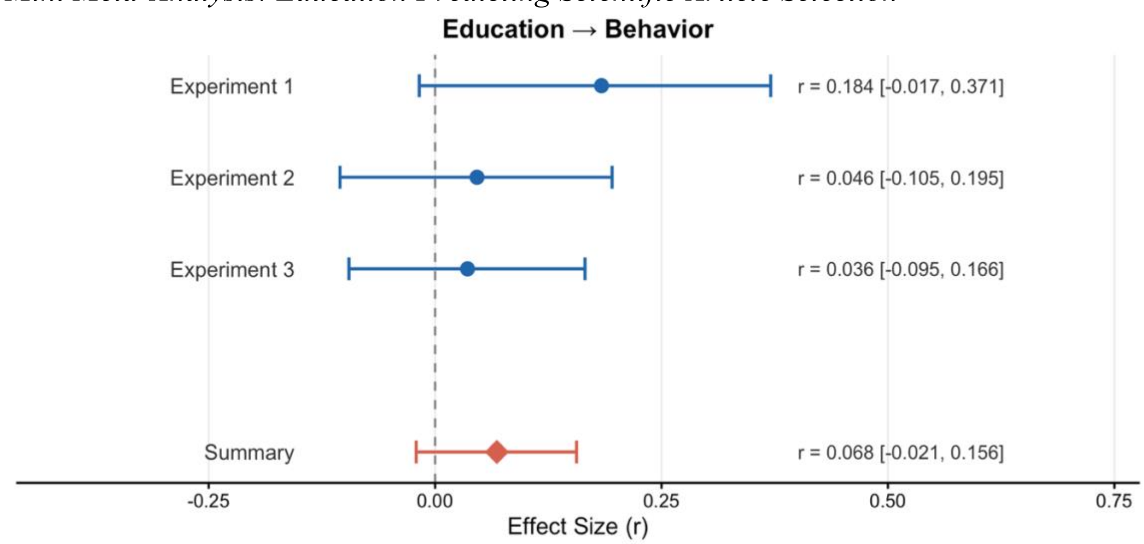
Mini Meta-Analysis: Religion Predicting Scientific Article Selection



Note. r estimated from ANOVA F-statistic and reflects magnitude of group differences only. The diamond represents the weighted mean effect; horizontal lines are 95% confidence intervals.

Figure 51

Mini Meta-Analysis: Education Predicting Scientific Article Selection



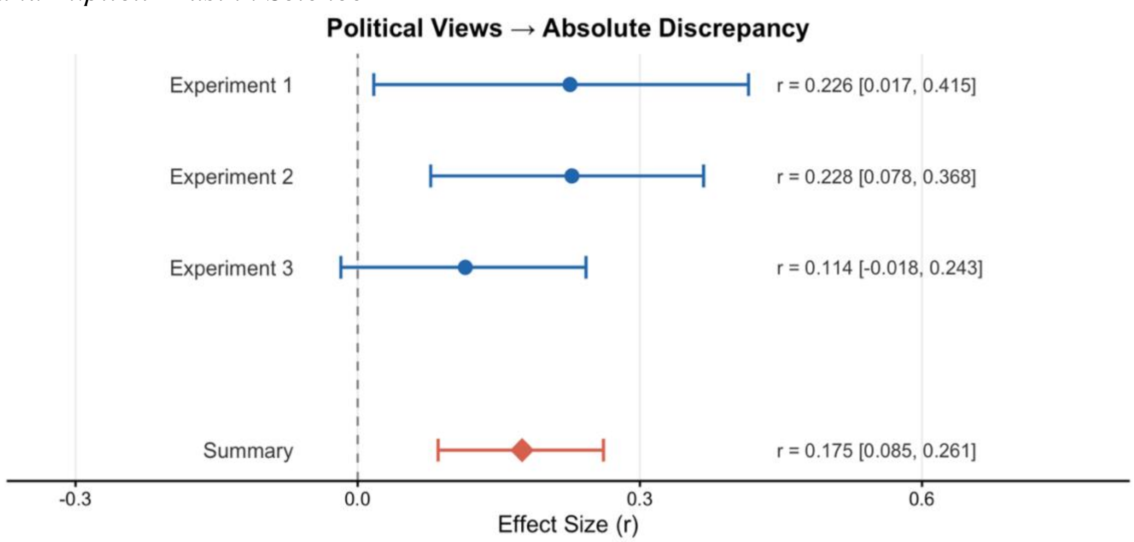
Note. r = Pearson correlation. Positive values indicate more education associated with more science articles selected. The diamond represents the weighted mean effect; horizontal lines are 95% confidence intervals.

Demographic Predictors of Implicit-Explicit Discrepancy

Absolute Discrepancy

Political orientation predicted absolute discrepancy of implicit-explicit: political views ($r = .18$, $p < .001$, $I^2 = 0.0\%$; see Figure 52) and political party ($r = .17$, $p < .001$, $I^2 = 39.6\%$; see Figure 53) both showed consistent cross-experiment effects, with conservatives and Republicans showing the greatest absolute discrepancy. Religion showed only a marginal summary effect on absolute discrepancy ($r = .08$, $p = .087$, $I^2 = 0.0\%$; see Figure 54).

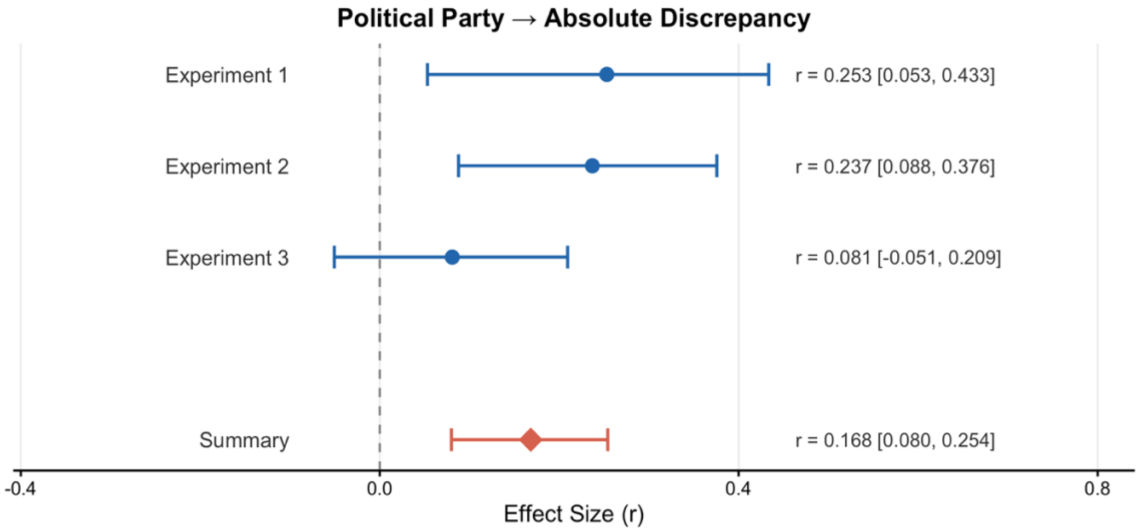
Figure 52
Mini Meta-Analysis: Political Views Predicting Absolute Discrepancy Between Implicit and Explicit Trust in Science



Note. Positive r = larger group differences in implicit-explicit alignment. The diamond represents the weighted mean effect; horizontal lines are 95% confidence intervals.

Figure 53

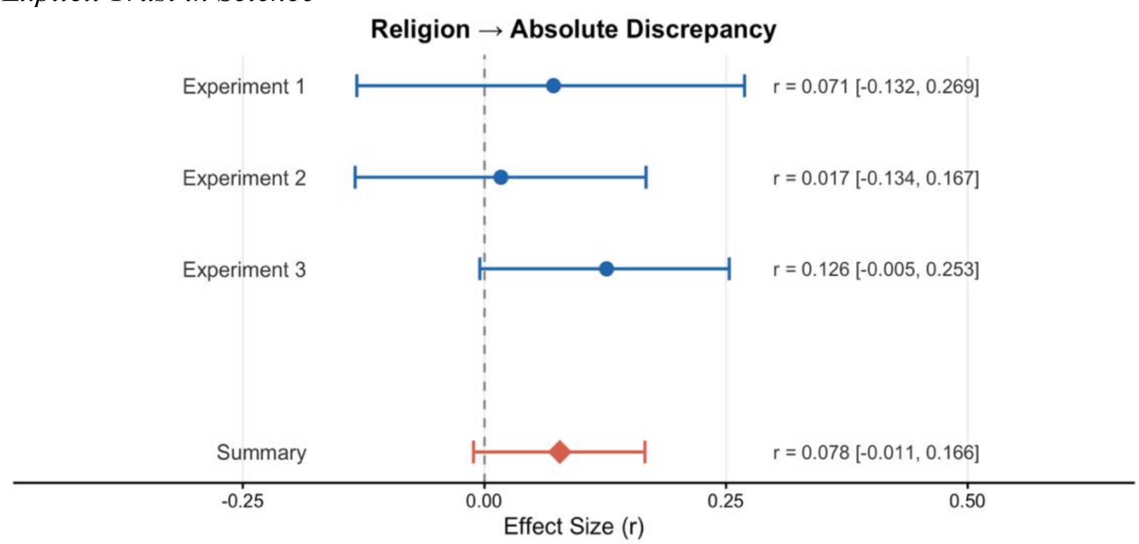
Mini Meta-Analysis: Political Party Predicting Absolute Discrepancy Between Implicit and Explicit Trust in Science



Note. Positive r = larger group differences in implicit-explicit alignment. The diamond represents the weighted mean effect; horizontal lines are 95% confidence intervals.

Figure 54

Mini Meta-Analysis: Religion Predicting Absolute Discrepancy Between Implicit and Explicit Trust in Science



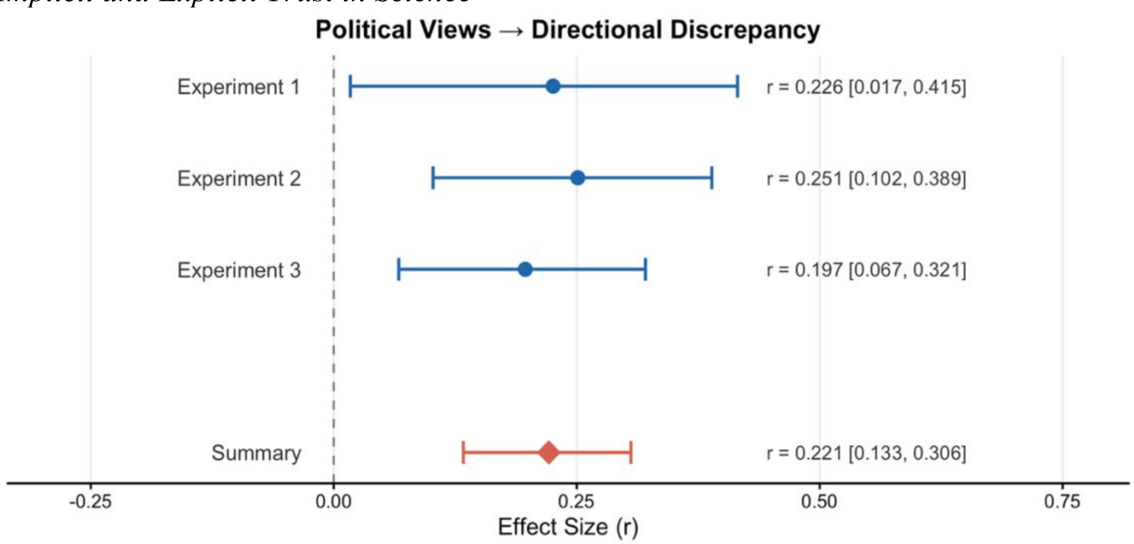
Note. Positive r = larger group differences in implicit-explicit alignment. The diamond represents the weighted mean effect; horizontal lines are 95% confidence intervals.

Directional Discrepancy

The direction of discrepancy was most strongly predicted by political views (r = .22, p < .001, I^2 = 0.0%; see Figure 55) and political party (r = .27, p < .001, I^2 = 0.0%; see Figure 56). Conservatives and Republicans showed positive directional discrepancy (implicit trust in science exceeding explicit trust) in all three experiments, while liberals and Democrats showed the reverse. Religion showed a small but significant summary effect on directional discrepancy (r = .10, p = .027; see Figure 57), though this was driven primarily by Experiment 2 (I^2 = 17.2%). This directional pattern suggests that political conservatives suppress explicit expressions of science trust relative to their implicit associations.

Figure 55

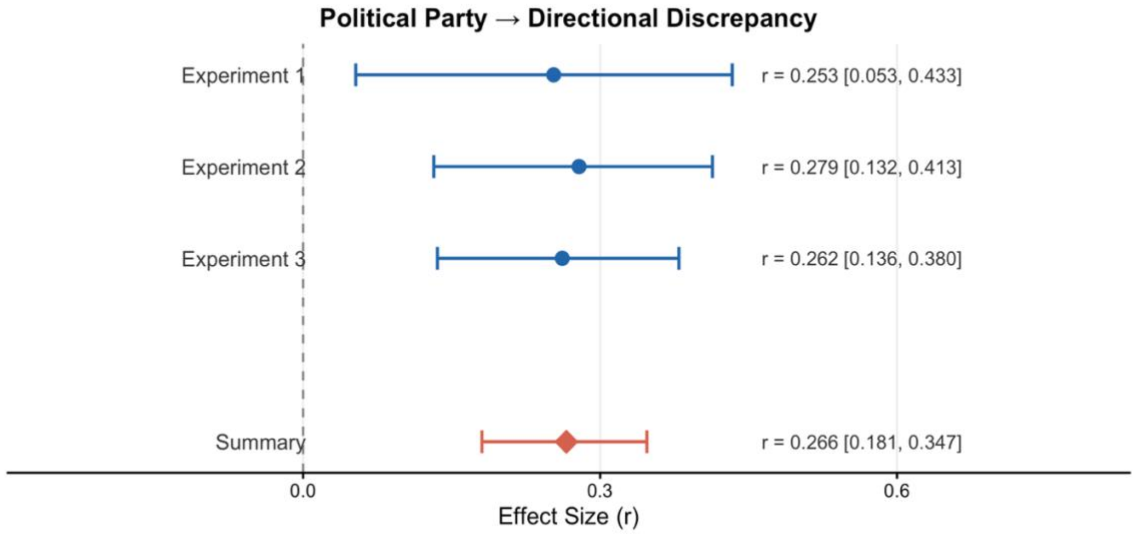
Mini Meta-Analysis: Political Views Predicting Directional Discrepancy Between Implicit and Explicit Trust in Science



Note. Positive r = larger group differences in implicit-explicit alignment. The diamond represents the weighted mean effect; horizontal lines are 95% confidence intervals.

Figure 56

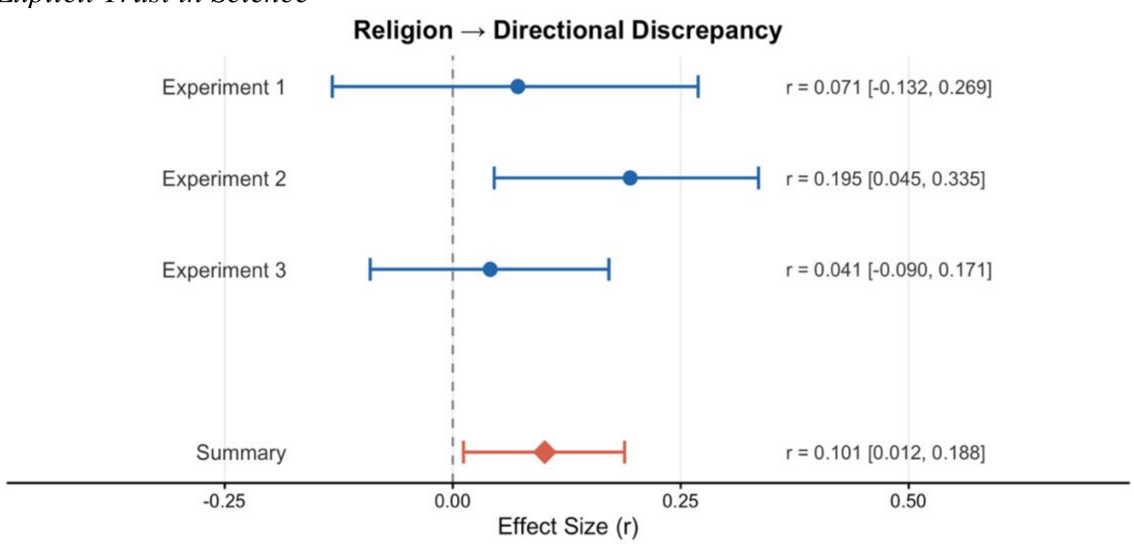
Mini Meta-Analysis: Political Party Predicting Directional Discrepancy Between Implicit and Explicit Trust in Science



Note. Positive *r* = larger group differences in implicit-explicit alignment. The diamond represents the weighted mean effect; horizontal lines are 95% confidence intervals.

Figure 57

Mini Meta-Analysis: Religion Predicting Directional Discrepancy Between Implicit and Explicit Trust in Science



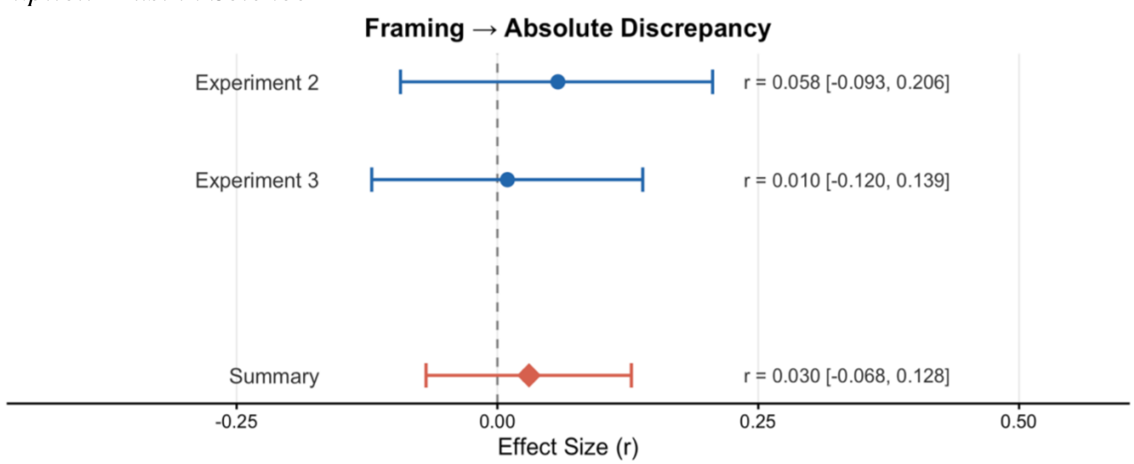
Note. Positive *r* = larger group differences in implicit-explicit alignment. The diamond represents the weighted mean effect; horizontal lines are 95% confidence intervals.

Framing and Uncertainty Effects on Discrepancy

Neither framing nor uncertainty affected either form of discrepancy. The meta-analytic summary for framing → absolute discrepancy and framing → directional discrepancy were both non-significant (r = .03, p = .548, I^2 = 0.0%; see Figure 58), (r = .06, p = .253, I^2 = 78.7%; see Figure 59), consistent with the individual experiment null results. In Experiment 3, uncertainty also had no significant effect on absolute discrepancy (r = .10, p = .135). Taken together, these results indicate that the experimental manipulations shifted the level of implicit trust in science without altering the gap between implicit and explicit trust.

Figure 58

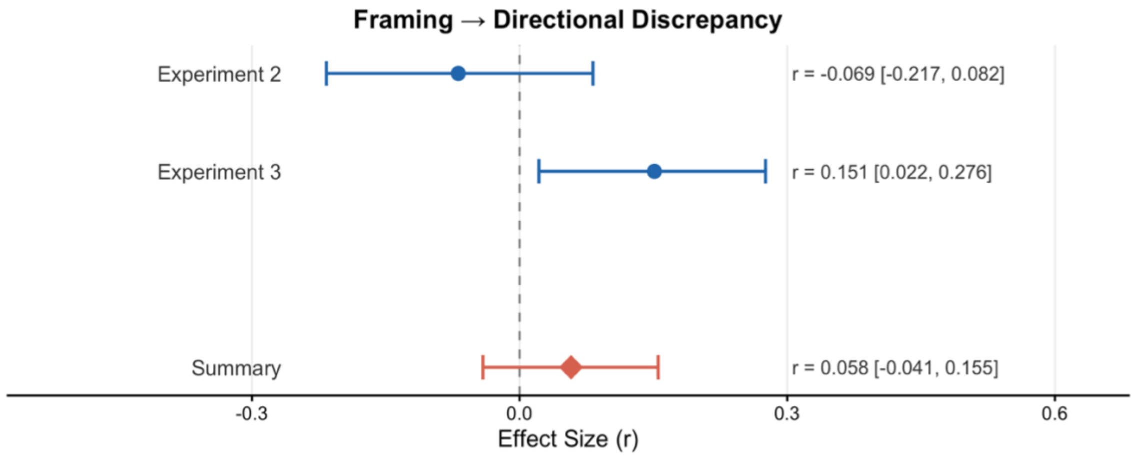
Mini Meta-Analysis: Framing Predicting Absolute Discrepancy Between Implicit and Explicit Trust in Science



Note. Positive r = larger differences between framing conditions in implicit-explicit alignment. The diamond represents the weighted mean effect; horizontal lines are 95% confidence intervals.

Figure 59

Mini Meta-Analysis: Framing Predicting Directional Discrepancy Between Implicit and Explicit Trust in Science



Note. Positive r = larger differences between framing conditions in implicit-explicit alignment. The diamond represents the weighted mean effect; horizontal lines are 95% confidence intervals.

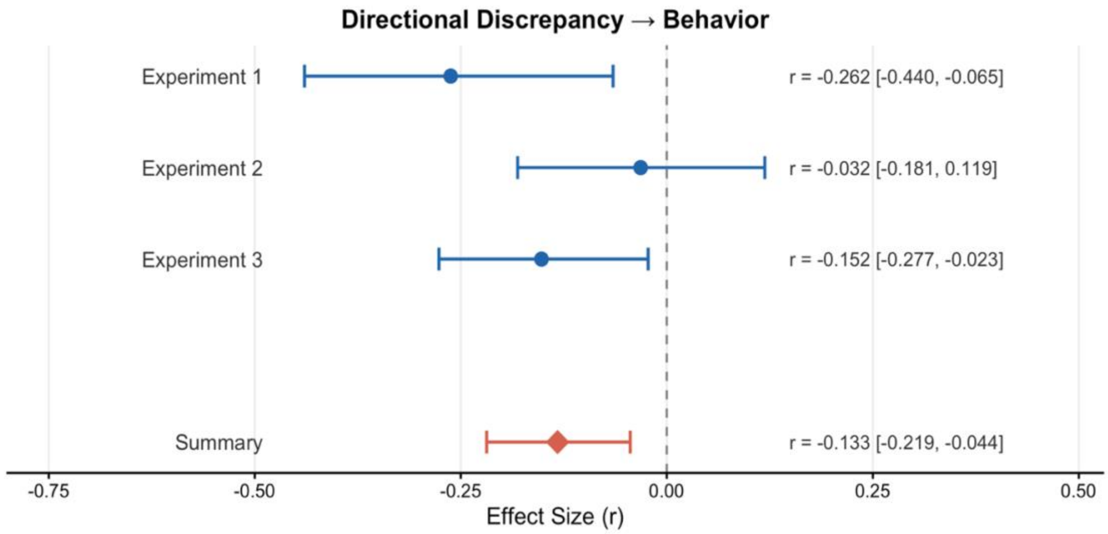
Discrepancy Predicting Science Article Selection

Directional discrepancy showed a significant negative summary effect on science article selection (r = -.13, p = .003; see Figure 60), indicating that participants whose implicit trust in science exceeded their explicit trust selected fewer science articles. This effect was significant in Experiments 1 and 3, and null in Experiment 2 (I^2 = 43.2%), though the consistent negative direction across all three experiments (even in Experiment 2 where it was non-significant) supports the robustness of the pattern.

Absolute discrepancy showed no significant relationship to science article selection either alone (r = -.02, p = .634; I^2 = 64.9%; see Figure 61) or when controlling for both trust measures (r = .03, p = .501, I^2 = 68.9%). Taken together, when the overall levels of implicit trust in science and explicit trust are held constant, the magnitude of misalignment does not predict science article selection above and beyond what each measure contributes separately. Only the direction of the gap carries behavioral significance. See Table 30 for summary of all mini meta-analysis effects.

Figure 60

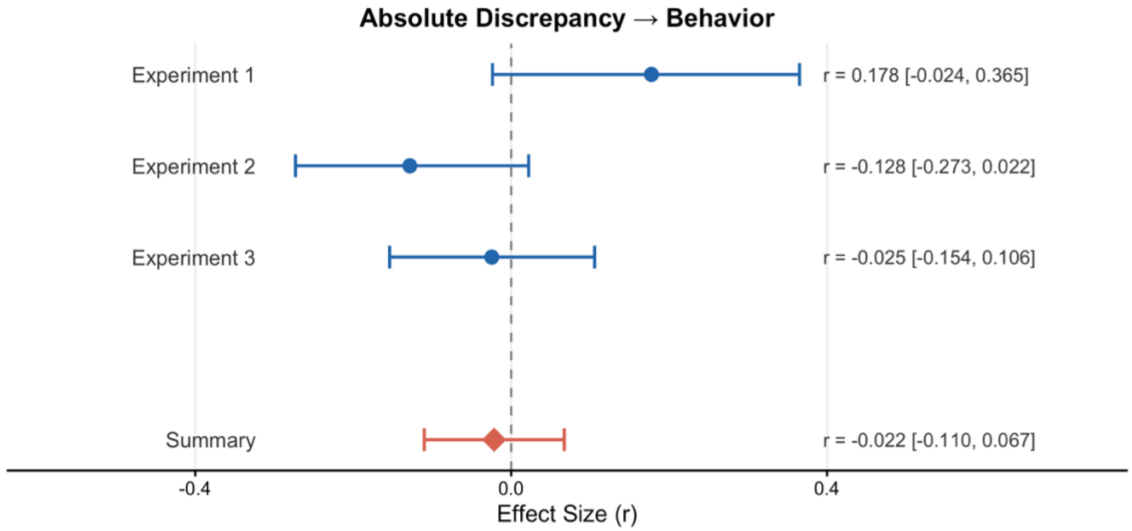
Mini Meta-Analysis: Directional Discrepancy Between Implicit and Explicit Trust in Science Predicting Science Article Selection



Note. Negative r = implicit trust exceeding explicit trust associated with fewer science articles selected. The diamond represents the weighted mean effect; horizontal lines are 95% confidence intervals.

Figure 61

Mini Meta-Analysis: Absolute Discrepancy Between Implicit and Explicit Trust in Science Predicting Science Article Selection



Note. Negative r = magnitude of discrepancy associated with fewer science articles selected. The diamond represents the weighted mean effect; horizontal lines are 95% confidence intervals.

Table 30

Summary of All Mini Meta-Analytic Effects Across Experiments

Effect	*k*	*r* [95% CI]	*p*	*Q* (*p*)	I^2
Implicit - Explicit trust correlation	3	.18 [.09, .26]	< .001	*Q* = 0.76 (*p* = .684)	0.0%
Implicit trust → behavior (adj. for explicit)	3	-.02 [-.11, .07]	.640	*Q* = 6.52 (*p* = .039*)	69.3%
Explicit trust → behavior (adj. for implicit)	3	.18 [.10, .27]	< .001	*Q* = 0.17 (*p* = .918)	0.0%
Framing → implicit trust	2	.18 [.08, .27]	< .001	*Q* = 1.50 (*p* = .220)	33.4%
Framing → explicit trust	2	.10 [.01, .20]	.040	*Q* = 2.61 (*p* = .106)	61.8%
Framing → behavior	2	.04 [-.06, .14]	.389	*Q* = 0.16 (*p* = .688)	0.0%
Political views → explicit trust	3	.34 [.26, .41]	< .001	*Q* = 3.03 (*p* = .220)	34.0%
Political party → explicit trust	3	.38 [.31, .46]	< .001	*Q* = 0.57 (*p* = .752)	0.0%
Religion → explicit trust	3	.23 [.14, .31]	< .001	*Q* = 1.75 (*p* = .416)	0.0%
Political interest → explicit trust	3	.22 [.13, .30]	< .001	*Q* = 1.25 (*p* = .535)	0.0%
Education → explicit trust	3	.03 [-.06, .12]	.470	*Q* = 5.94 (*p* = .051†)	66.3%
Political views → implicit trust	3	.01 [-.09, .10]	.908	*Q* = 2.29 (*p* = .318)	12.8%
Political party → implicit trust	3	.11 [.02, .20]	.015	*Q* = 1.34 (*p* = .511)	0.0%
Religion → implicit trust	3	.05 [-.04, .14]	.243	*Q* = 1.08 (*p* = .582)	0.0%
Political interest → implicit trust	3	.16 [.07, .25]	< .001	*Q* = 0.05 (*p* = .975)	0.0%
Education → implicit trust	3	.10 [.01, .18]	.035	*Q* = 0.68 (*p* = .710)	0.0%
Political views → behavior	3	-.11 [-.20, -.02]	.015	*Q* = 1.24 (*p* = .537)	0.0%
Political party → behavior	3	.11 [.02, .19]	.020	*Q* = 1.99 (*p* = .371)	0.0%
Political interest → behavior	3	.15 [.06, .23]	.001	*Q* = 0.70 (*p* = .705)	0.0%
Religion → behavior	3	.15 [.06, .23]	.001	*Q* = 1.16 (*p* = .561)	0.0%
Education → behavior	3	.07 [-.02, .16]	.133	*Q* = 1.60 (*p* = .449)	0.0%
Political views → absolute discrepancy	3	.18 [.09, .26]	< .001	*Q* = 1.56 (*p* = .458)	0.0%
Political party → absolute discrepancy	3	.17 [.08, .25]	< .001	*Q* = 3.31 (*p* = .191)	39.6%
Religion → absolute discrepancy	3	.08 [-.01, .17]	.087†	*Q* = 1.16 (*p* = .561)	0.0%
Political views → directional discrepancy	3	.22 [.13, .31]	< .001	*Q* = 0.30 (*p* = .860)	0.0%
Political party → directional discrepancy	3	.27 [.18, .35]	< .001	*Q* = 0.05 (*p* = .974)	0.0%
Religion → directional discrepancy	3	.10 [.01, .19]	.027	*Q* = 2.41 (*p* = .299)	17.2%
Framing → absolute discrepancy	2	.03 [-.07, .13]	.548	*Q* = 0.23 (*p* = .635)	0.0%
Framing → directional discrepancy	2	.06 [-.04, .16]	.253	*Q* = 4.70 (*p* = .030*)	78.7%
Uncertainty → absolute discrepancy (Exp. 3 only)	1[1]	.10	.135	—	—
Directional discrepancy → behavior	3	-.13 [-.22, -.04]	.003	*Q* = 3.52 (*p* = .172)	43.2%
Absolute discrepancy → behavior (alone)	3	-.02 [-.11, .07]	.634	*Q* = 5.70 (*p* = .058†)	64.9%
Absolute discrepancy → behavior (adj.) ,	3	.03 [-.06, .12]	.501	*Q* = 6.43 (*p* = .040*)	68.9%

Note. All effects converted to Pearson *r* following Goh, Hall, & Rosenthal (2016). Weighted mean *r* uses Fisher *r*-to-*z* transformation weighted by (n - 3). 95% CIs are Fisher-transformed and back-converted. *Q* = Cochran's heterogeneity statistic; I^2 = proportion of variance due to heterogeneity. [1]Single experiment; no meta-analysis performed. †$p < .10$. *$p < .05$

General Discussion

In an era marked by widespread misinformation, political polarization, and declining trust in science, understanding how people evaluate and trust science is more critical than ever. Trust in science shapes public health decisions, policy support, and people's judgments about expertise and credibility. Despite the important role trust in science plays in modern society, relatively little work has examined what psychological processes underly how people trust science. Much of the existing literature relies heavily on explicit self-report measures, often treating trust in science as a singular construct that can be adequately captured through direct questioning alone. My dissertation aimed to move beyond this assumption by examining people's implicit and explicit trust in science across different communication methods and uncertainty contexts.

Across three experiments, the goal of my dissertation was to address three key questions: (1) Do implicit and explicit trust in science reflect distinct cognitive processes that predict science-related choices? (2) How does framing communication messages influence implicit and explicit trust and science-related behavior, and does scientific knowledge play a moderating role? and (3) How does uncertainty interact with framing messages and scientific knowledge to influence implicit and explicit trust and science-related behavior?

Several important findings emerged across the experiments. First, implicit and explicit trust in science capture distinct cognitive processes with independent predictive validity for science-related behavior, emphasizing the value of moving beyond self-report alone. Second, framing science as something that is dynamic and changing leads to higher implicit and explicit trust in science compared to static framing, though it should be noted that Experiments 2 and 3 differ on the implicit and explicit effects. Third, uncertainty decreases explicit trust in science, but science process skills serve as a meaningful individual difference that buffers against the trust-reducing effects of uncertainty. However, when looking at behavior, uncertainty and framing interact with science process skills in an unexpected way, such that people higher in science skills choose fewer scientific articles when uncertainty is high and science is framed as dynamic. And fourth, the implicit-explicit discrepancy is shaped by political identity and religion in ways that speak directly to social desirability as a driver of explicit trust responses.

Taken together, the findings suggest that trust in science appears to reflect multiple cognitive evaluation processes shaped by communication context, interpretations of uncertainty, understanding of the scientific process, and broader social identities. My dissertation therefore contributes not only to the psychological and trust in science literatures, but also to broader efforts that inform how we can rebuild the public's trust in science.

Implicit and Explicit Trust in Science as Distinct Cognitive Processes

One of the primary contributions of my dissertation is that implicit and explicit trust in science reflect distinct cognitive processes that each contribute unique variance to science-related behavior. Although trust in science research has historically relied heavily on explicit self-report measures, the present findings suggest that explicit measures capture only one aspect of how people evaluate and trust science. Across all three experiments, implicit and explicit trust in science did not consistently converge, did not respond identically to manipulations, and did not predict behavior in the same way. These findings align with dual-process perspectives suggesting that evaluations can arise from both associative and propositional processes (Gawronski & Bodenhausen, 2006, 2009). Applied to trust in science, this means that people may hold automatic associations between science and trustworthiness that differ from their more deliberate trust of science. Therefore, the divergence between implicit and explicit trust in science is theoretically meaningful because it suggests that people may automatically associate science with trust in ways that do not always align with their reflective trust in science.

Experiment 1 provided the clearest evidence for this distinction. Both implicit and explicit trust in science independently predicted science article selection, together accounting for 10% of variance. Furthermore, the hierarchical regression analyses reinforced this interpretation, showing that each measure explained roughly equal unique variance (≈ 6%) and that each measure contributed additional explanatory power beyond the other. Taken together, these findings support the broader argument that trust in science should not be conceptualized as a singular process operating uniformly to affect people's science-related behavior.

The direction of the implicit trust in science effect, however, was not what I expected: participants with stronger implicit associations between science and trustworthiness selected *fewer* science articles. This pattern held consistently across nearly all explicit measures in the exploratory analyses, making it difficult to dismiss as a statistical anomaly. One possible interpretation is a "complacency" effect. If someone implicitly associates science with trustworthiness, they may feel that science is, in a sense, already handled and does not require active engagement or information seeking. According to the MODE model (Fazio, 1990; Fazio & Olson, 2014), behavior is more likely to be guided by automatic associations when motivation to think carefully is low. For someone whose gut-level trust in science is already strong, the motivation to actively seek out science content may be weaker. This theoretically-based idea suggests that implicit trust in science operates differently from explicit trust in its downstream behavioral consequences, which is precisely the kind of dissociation that dual-process frameworks predict.

A second, complementary interpretation involves the implicit-explicit discrepancy findings. The directional discrepancy, where implicit trust exceeded explicit trust, predicted fewer science article selections in Experiments 1 and 3. This pattern suggests that part of the negative implicit-behavior relationship observed in Experiment 1 may be driven by people whose explicit trust in science is lower than their implicit trust and whose behavior more closely tracks the explicit, socially influenced response. I return to this interpretation in the paragraphs below reflecting on implicit-explicit discrepancy, political identity, and social desirability.

Finally, the behavioral task itself may partially explain the negative relationship between implicit trust in science and behavior. The news article selection task measured selective engagement with science-related headlines rather than general trust in science directly. Choosing a science-related article likely involves multiple cognitive processes beyond trust alone, including curiosity, novelty seeking, relevance, cognitive effort, political identity, and interest in science topics. The behavioral measure therefore may capture a more complex form of science engagement than originally anticipated.

The exploratory demographic analyses further demonstrate that implicit and explicit trust in science are distinct cognitive processes. Across experiments, political orientation and religion consistently related to explicit trust in science and, in some cases, implicit trust in science as well. Political orientation and religion strongly and consistently predicted explicit trust in science: conservatives, Republicans, and Christians reported lower explicit trust in science than liberals, Democrats, and non-religious participants in every sample. These findings align with prior research demonstrating that trust in science is shaped partly by ideological identity, group norms, and broader cultural narratives surrounding scientific institutions (DiMaggio et al., 2018; O'Brien & Noy, 2025).

Importantly, the relationships between demographics and trust in science were much stronger for explicit trust measures than for implicit trust measures. While no demographic variable significantly predicted implicit trust in science in any individual experiment, the mini meta-analysis reveals small but consistent associations between political identity and implicit trust in science. This pattern is theoretically meaningful and should not be attributed solely to the SC-IAT's limited sensitivity; the effects not reaching significance within any individual experiment is likely due to limited statistical power. This is the pattern I would expect if the true implicit effect is real but small, which is exactly what the implicit-explicit literature predicts: implicit-explicit correlations are weakest in socially sensitive domains where social desirability pressures are highest (Nosek, 2007).

The implicit-explicit discrepancy findings sharpen this picture further. Conservatives and Republicans showed higher implicit trust in science than explicit trust in science across all three experiments, while liberals and Democrats showed the reverse, albeit at a smaller magnitude. This suggests that conservatives and Christians hold stronger implicit associations between science and trust than they report explicitly; their gut-level trust in science is higher than their stated trust in science, potentially because explicit trust in science is shaped by political group norms and social pressures in ways that implicit associations are not. As Nosek (2007) demonstrated, implicit-explicit correspondence is weakest in domains with high social sensitivity, where deliberate reasoning is more likely to override implicit responses in the direction of social acceptability for one's group. Trust in science is now exactly such a domain; the COVID-19 pandemic was really the start of the decline of trust in science, followed by the second election of Trump into office, meaning this is a newer shift in social desirability and broader societal expectations related to science by political or religious group, further supporting why we might be seeing this discrepancy between implicit and explicit trust in science in this unique moment in time.

Taken together, these patterns support a social desirability account of the implicit-explicit trust in science divergence. Explicit trust in science may reflect not only personal beliefs but also external pressure to align with the positions of one's political or religious community, which Fisher (1993) and Furnham (1986) identified as a core vulnerability of self-report measures in politically sensitive domains. Implicit trust in science, by contrast, may be less susceptible to these pressures, capturing associations that are less easily controlled. The finding that the implicit-explicit gap predicted science article selection in Experiments 1 and 3, such that those whose implicit trust exceeded their explicit trust selected fewer science articles, adds a behavioral dimension to this interpretation: people whose implicit trust in science is higher than what they report explicitly may be the very people who most suppress science-oriented behavior in line with their group's norms, rather than their own gut-level trust in science feelings. Taken together, this further strengthens the argument that implicit and explicit trust in science may emerge through partially overlapping but distinct associative processes.

The findings also align with the Associative-Propositional Evaluation (APE) model (Gawronski & Bodenhausen, 2006, 2009). According to the APE model, implicit evaluations arise primarily from associative processes, whereas explicit evaluations emerge through propositional reasoning about whether beliefs are valid or accurate. Applied to trust in science, individuals may automatically associate science with trustworthiness while consciously questioning certain scientific institutions, or they may explicitly endorse trust in science while still holding automatic skepticism shaped by broader cultural or political narratives. The present findings support the relevance of these dual-process perspectives for understanding trust in science.

I want to clearly acknowledge that the conclusions I'm drawing about implicit and explicit trust in science do not suggest that implicit measures are inherently superior to explicit measures. Rather, the findings suggest that each captures different aspects of trust in science. Explicit trust measures consistently predicted science-related behavior in theoretically meaningful ways and were often more sensitive to communication manipulations than implicit measures. Instead of framing implicit and explicit measures as competing approaches, the findings from my dissertation support a framework in which each measure contributes unique insight into how people evaluate and trust science.

Implicit and explicit trust in science being unique cognitive processes that operate under different conditions has important implications for science communication and public engagement efforts. Because implicit trust in science is understudied and not well understood, interventions to increase the public's trust in science thus far only focus on changing people's explicit trust in science through communication messaging, scientific source information, or individual knowledge (Iordanou et al., 2026). However, if trust in science also involves automatic associative processes, then interventions targeting only explicit trust in science may not fully capture how people evaluate scientific information in everyday contexts. Understanding how implicit and explicit trust processes operate, influence behavior, and are influenced by interventions are therefore critical for developing more effective approaches to science communication.

Overall, from the findings across the three experiments, I can conclude that trust in science reflects multiple cognitive evaluation processes rather than a single unified construct. Implicit and explicit trust in science each provide meaningful but distinct information about how people evaluate science and engage with science-related information. These findings provide a conceptual and methodological foundation for future work examining how different forms of trust in science develop, interact, and shape behavior.

Communication Framing Shapes Trust in Science

A second major contribution of this dissertation is demonstrating that the way science is communicated can meaningfully shape trust in science. Across Experiments 2 and 3, framing science as dynamic and evolving generally increased implicit and explicit trust in science relative to framing science as static and unchanging. This finding was not what I originally hypothesized; I predicted that static framing would be associated with higher trust on the grounds that consistency and certainty would foster more confidence in science compared to science changing over time which might introduce more unsettled feelings. Instead, the results suggest the opposite, but in retrospect, this pattern is well-aligned with the broader dynamic norms literature. Sparkman and Walton (2017, 2019) demonstrated that framing information around a changing trend (dynamic norm framing) increases positive attitudes and behavior change compared to a stable state (static norm framing), and my findings extend this logic to both implicit and explicit trust in science. Taken together, these findings contribute to a growing body of work suggesting that communication framing shapes how people evaluate and trust science.

Importantly, the communication framing findings challenge a common assumption that uncertainty in scientific results or changing evidence undermines trust in science. There are mixed findings when it comes to communicating uncertainty in science (Iordanou et al., 2026), but a lot of researchers and public scientific communicators attempt to present scientific findings as stable and certain (Jamieson, 2017). Concerns often arise that acknowledging scientific revision or uncertainty may reduce public confidence in science. However, the present findings are among the first to directly manipulate the framing of science and the findings show that framing science as evolving and self-correcting may actually strengthen several dimensions of trust.

One interpretation is that transparency in the scientific process functions as a signal of intellectual honesty and good faith (Grand et al., 2012); when scientists acknowledge what is not yet known in science, people may interpret this acknowledgement not as weakness but as credibility. This is consistent with research on communicator credibility, where transparency about uncertainty can increase rather than decrease trust when the communicator is perceived as acting in good faith (Steijaert et al., 2020). The exploratory subscale findings converge with this interpretation.

Participants exposed to dynamic framing generally perceived scientists as more open, competent, and benevolent than participants exposed to static framing. These findings suggest that emphasizing the evolving nature of science may communicate transparency, intellectual honesty, and responsiveness to evidence. Of the four subscales, the most consistent framing effect emerged for perceived openness. Participants in the dynamic framing condition consistently viewed scientists as more willing to be transparent and open about scientific information. This finding is theoretically important because openness is closely tied to perceptions of legitimacy and institutional trustworthiness. Framing science as a process that evolves in response to evidence may signal that scientists are willing to revise conclusions rather than rigidly defend fixed positions.

That said, looking at the meta-analytic effects, dynamic framing consistently increased implicit trust in science relative to static framing, whereas dynamic framing also increased trust in a similar direction for explicit trust, but with substantially more variability across studies, yielding a marginal weighted summary. This pattern across experiments is worth unpacking carefully. In Experiment 2, framing significantly affected explicit trust in science but only produced a directional, non-significant shift in implicit trust in science. In Experiment 3, this pattern essentially reversed: framing produced a significant effect on implicit trust in science but no effect on explicit trust in science. Rather than treating this as an inconsistency, this crossover pattern may be theoretically informative.

One possibility is that the addition of the uncertainty manipulation in Experiment 3 changed the processing conditions in ways that differentially engaged implicit versus explicit responding. Specifically, when participants are simultaneously processing information about how science is framed and how uncertain the context is, explicit trust, which is more strongly anchored to political identity and religious beliefs, may be more likely to default to those stable prior anchors rather than updating in response to the framing. While implicit attitudes used to be characterized as slow to update (e.g., Wilson et al., 2000), the implicit impression formation literature tells a more nuanced story: automatic associations can shift rapidly in response to immediate contextual cues, particularly when those cues directly implicate the evaluation target (for reviews, see Cone et al., 2017; Ferguson et al., 2019). In this sense, a framing manipulation that directly changes how science is characterized may be similar to the kind of contextual signal that automatic associations are sensitive to. In these experiments, then, implicit trust may be more sensitive to immediate contextual signals, and the combination of dynamic framing with uncertainty may have created precisely the kind of direct informational cue that shifts implicit responses. Future research should directly test how framing and uncertainty both interact and operate separately on implicit and explicit trust in science. Moreover, future research should explore other types of contextual or informational manipulations to see how slowly or rapidly implicit and explicit trust in science can be shifted.

Furthermore, in the manipulation check result in Experiments 2 and 3, static framing was rated as more clear than dynamic framing, which also raises the possibility that a dynamic framing of science was perceived as more ambiguous or complex, which could weaken explicit trust responses. This reiterates the importance of future research examining how variations to the framing and uncertainty manipulations relate to implicit and explicit trust in science and science-related behavior.

The exploratory demographic findings also raise important questions regarding the interaction between communication framing and social identity. No significant effects emerged showing that different demographic groups respond differently to communication framing or uncertainty contexts. While this has promising initial interpretation, such that the same framing or uncertainty interventions can be applied to multiple demographic groups, future work should continue to examine this more rigorously. Understanding what shapes trust in science requires integrating cognitive, social, political, and cultural perspectives simultaneously.

Critically, the framing and uncertainty manipulations did not affect the size or direction of the implicit-explicit discrepancy. This suggests that these experimental contexts shifted the *level* of implicit trust and explicit trust without altering the *gap between* implicit and explicit trust. Instead, individual characteristics, such as political identity, appear to determine the implicit-explicit gap rather than immediate situational factors. The implications here are significant: science communication interventions may be capable of shifting implicit and explicit trust in science, but the deep structural alignment of explicit trust with political and religious identity may require different interventions altogether.

Another important aspect of the framing findings is that changes in implicit and explicit trust in science did not consistently translate into changes in science article selection behavior. One explanation for why this might be comes back to the MODE model (Fazio, 1990; Fazio & Olson, 2014), which holds that the relationship between attitudes and behavior depends on motivation and opportunity to deliberate. An article selection task in an online survey likely affords participants sufficient time and motivation to deliberate, but the key insight is that under high deliberation, behavior is more likely to follow from *existing, well-established* evaluations than from recently activated evaluations. Implicit and explicit trust in science shifting from the framing manipulation might reflect fresh, single-exposure changes that may not yet carry the motivational weight of long-held beliefs. This aligns with the idea that attitude strength and stability, not just attitude direction, are critical determinants of behavioral follow-through (Krosnick & Petty, 1995).

Another possibility is that implicit and explicit trust in science and science engagement behavior are related but distinct constructs. Behavioral engagement with science-related information likely depends on numerous factors beyond trust alone, including interest, cognitive effort, relevance, emotional salience, media consumption habits, and/or topic-specific motivations. Thus, even when communication framing shapes how people trust science, those shifts may not automatically translate into changes in selective information behavior. Finally, the article selection came at the end of the experiments, which means the framing effects may have dissipated by then. The pathway from trust in science change, whether implicit or explicit, to behavioral change may therefore require repeated exposures and/or stronger manipulations to manifest. Future research should explore these possibilities.

More broadly, the findings suggest that people may not necessarily expect science to provide perfect certainty or fixed conclusions. Instead, people may value transparency, openness, and responsiveness to evidence. Communicating science as dynamic may therefore align more closely with how many people expect trustworthy scientists and scientific institutions to behave. These findings have significant implications for science communication interventions aimed at increasing the public's trust in science and should continue to be explored in future research.

Understanding Science Shapes Reactions to Uncertainty

A third major contribution of my dissertation is demonstrating that people's reactions to scientific uncertainty depend in part on how they understand science as a process. Although contexts of uncertainty undermine trust in science, the present findings suggest that reactions to uncertainty are more nuanced and depend on individual differences in science process skills. Across analyses in Experiment 3, science process skills emerged as a consistent predictor and moderator of trust in science, whereas objective scientific knowledge did not show any patterns. Science process skills consistently moderated how uncertainty affected explicit trust: under high uncertainty, participants with lower science skills showed significantly reduced trust across multiple explicit measures, while those with higher science skills were largely unaffected. This "protective" effect replicated across the explicit trust composite, the explicit science trust-suspicious scale, the 4-dimensional overall score, and perceived benevolence and competence, suggesting a robust pattern. These findings suggest that understanding how science works may be more important for maintaining trust in science than knowing scientific facts.

This distinction is theoretically important because discussions of public trust in science often focus heavily on factual knowledge deficits or scientific literacy. Many interventions aimed at improving trust in science attempt to increase knowledge of scientific information or correct misinformation (Iordanou et al., 2026). However, the findings from Experiment 3 suggest that understanding the scientific process itself may play a particularly important role in shaping how people interpret scientific uncertainty and changing evidence. Science process skills involve understanding how scientific knowledge develops through evidence evaluation, revision, testing, and replication. People with stronger science process skills may therefore view uncertainty as a normal and expected aspect of scientific inquiry rather than as evidence of incompetence or unreliability. This finding adds an important qualification to prior work treating scientific knowledge as uniformly protective against trust erosion.

Importantly, however, science process skills did not simply protect people from all negative effects of uncertainty. While research has shown that higher trust in science and better scientific reasoning skills buffer against misinformation and conspiracy beliefs (Čavojová et al., 2023; Rosman & Grösser, 2023), the Experiment 3 findings also suggest the relationship is more nuanced: stronger science skills protect against uncertainty-induced *reduction* in explicit trust, but they do not insulate people from all negative effects of uncertainty. Under high uncertainty, dynamic framing also reduced science article selection for participants higher in science skills but had no effect for participants lower in science skills.

One interpretation of the behavioral finding is that people who are highly skilled in science may interpret uncertainty signals more informationally, recognizing that if science is presented as changing under a condition of uncertainty, it means definitive conclusions are not yet available, making active engagement with science content premature. For people who are lower in science skills, the same signals may carry less informational weight, leaving behavior unchanged. This is not the same as saying people higher in science skills are simply more skeptical of science in general; indeed, their explicit trust is buffered rather than reduced under uncertainty. Rather, it suggests that having and understanding the skills of science may make people more responsive and calibrated to contextual signals about the state of evidence, and this can manifest differently depending on whether the outcome is an attitude or a behavior.

Importantly, the findings suggest that uncertainty itself does not uniformly undermine trust in science. Instead, uncertainty appears to interact with how people interpret the purpose and function of scientific inquiry. Some people may interpret uncertainty as evidence that science is functioning appropriately by updating conclusions in response to evidence whereas others may interpret the same uncertainty as evidence that science is unreliable or politically motivated. The COVID-19 pandemic, a time of great uncertainty and "unprecedented times," provides an especially relevant real-world context for interpreting these findings. During the pandemic, scientific recommendations frequently changed in response to emerging evidence regarding masks, vaccines, viral transmission, and treatment approaches. For some people, these revisions likely reflected the normal operation of scientific inquiry under rapidly evolving conditions. For others, changing recommendations may have appeared inconsistent and confusing, creating more feelings of suspicion and mistrust in science. The findings from my dissertation suggest that differences in science process skills may partially explain why individuals reacted differently to scientific uncertainty during periods of rapid scientific change. People with stronger understanding of how science works may have been more likely to interpret changing recommendations as evidence of scientific responsiveness rather than evidence of institutional failure.

At the same time, the findings also suggest that science communication alone may not fully determine how uncertainty affects trust in science. Individual differences in scientific understanding shape how people interpret scientific communication. Thus, identical uncertainty messages may produce very different trust responses depending on the audience's understanding of scientific processes. The findings also help clarify why objective scientific knowledge and science process skills did not behave identically across analyses: objective knowledge measures assess factual scientific information, whereas science process skills assess understanding of how scientific inquiry operates. People may possess factual scientific knowledge without fully understanding how scientific evidence changes over time. The stronger role of science process skills across analyses suggests that understanding scientific reasoning and evidence evaluation may be especially important for fostering resilient trust in science. Therefore, my dissertation findings support arguments that science education should emphasize scientific reasoning and process understanding rather than memorization of isolated facts alone.

Another important implication of these findings is that public trust in science may be strengthened by helping people better understand why scientific uncertainty occurs. Communication efforts often present uncertainty as a weakness or communication challenge that should be minimized. However, the present findings suggest that uncertainty may be interpreted more positively when individuals understand it as a natural consequence of scientific inquiry. Future science communication efforts may therefore benefit from more explicitly explaining how scientific evidence develops, why scientific conclusions sometimes change, and how uncertainty contributes to scientific progress. Rather than attempting to eliminate public awareness of uncertainty, communication efforts may be more effective when uncertainty is contextualized within the broader process of scientific reasoning.

It is also worth noting that the Science Process Skills Inventory is a self-report measure, and it is possible that it captures some degree of science identity or science enthusiasm in addition to, or instead of, actual science process skills. Whether the buffering effect is better explained by knowing how science works, or by identifying strongly with science as a social group, is a question that future research should address. Scales like the Science Process Skills Inventory that target process understanding were designed to minimize this confound, but without measuring science identity in any way, it could be playing a factor, which should be addressed in future research. Taken together, these findings suggest that understanding science as a process plays a critical role in shaping reactions to uncertainty. Trust in science depends not only on what scientific information is communicated, but also on how individuals interpret scientific revision, uncertainty, and evidence change.

Methodological Contributions

Beyond the theoretical contributions, my dissertation also contributes methodologically to the study of trust in science. This is, to my knowledge, the second study to investigate implicit trust in science and the first to investigate how implicit and explicit trust in science predicts a science-related behavioral choice and how both can be influenced by science communication and uncertainty contexts. Previous work by Schoor and Schütz (2021) demonstrated that implicit trust in science predicted science knowledge beyond explicit measures. The findings from my dissertation extend this work by demonstrating that both implicit and explicit trust in science relate to behavior, are influenced by communication framing and uncertainty contexts, and differ meaningfully by demographic groups. More broadly, these findings suggest that implicit trust in science is not fully captured through explicit measures, paving the way for new methods of measuring trust in science.

At the same time, the findings across my three experiments also highlight some of the challenges involved in measuring implicit trust in science. The unexpected negative relationship between implicit trust in science and science article selection suggests that implicit measures may capture broader institutional or associative meanings beyond simple trustworthiness associations. Future work should continue to explore and refine implicit trust in science measures and examine what specific automatic associations these tasks capture.

Another methodological contribution involves incorporating a behavioral measure of science engagement. Much of the existing trust in science literature relies exclusively on self-report outcomes. By including the science article selection task as a dependent variable in Experiments 2 and 3, my dissertation attempted to move beyond self-report as the only outcome science communication and uncertainty might influence. Although the behavioral findings were more complex than anticipated, incorporating behavioral measures remains important for understanding how trust in science influences real-world engagement with scientific information. Future work should continue developing behavioral measures that capture different forms of science engagement, including media consumption, information sharing, policy support, health behavior, and responses to misinformation.

Furthermore, I was able to examine experimentally manipulated communication and uncertainty contexts with multiple forms of trust assessment. By looking at all of these together, I was able to examine how communication, context, implicit and explicit trust in science, and behavioral outcomes interact. Importantly, the findings demonstrate that implicit, explicit, and behavioral measures each captured somewhat different aspects of how people trust and interact with science. These findings reinforce the importance of using multiple methods simultaneously rather than assuming any single measure fully captures trust in science.

Additionally, my dissertation examines multiple dimensions of explicit trust in science and scientists, including competence, integrity, benevolence, and openness. The findings suggest that communication framing may influence these dimensions differently, highlighting the importance of conceptualizing trust in science as multidimensional rather than monolithic. Finally, the dissertation contributes methodologically by integrating science communication manipulations with measures of science process skills. Examining how understanding of scientific inquiry interacts with communication framing and uncertainty provides a more nuanced framework for understanding public trust in science.

Overall, the methodological contributions of my dissertation support a broader shift toward more in-depth, multi-method approaches to studying trust in science. Understanding a full picture of how people trust science likely requires integrating multiple forms of measurement, multiple theoretical frameworks, and multiple communication contexts.

Limitations and Future Directions

I want to acknowledge several limitations of the present research. At the same time, these limitations point to important future directions for research on implicit and explicit trust in science, science communication, and uncertainty. Broadly, future work should replicate and extend these experiments with larger samples, stronger manipulations, and more diverse methodological approaches to establish the robustness of the framing and uncertainty effects on implicit and explicit trust in science and clarify the conditions under which these effects extend to behavior.

Samples and Generalizability

First, I recruited participants in all three experiments from CloudResearch Connect, which, while more diverse than undergraduate samples, does not represent the full range of the U.S. population, particularly those with very low education or limited internet access. Furthermore, participants on CloudResearch are opting into a scientific research study, which likely reflects a different disposition toward science. Generalizability to populations with different levels of trust in science therefore remains an open question, and future research should recruit more diverse populations.

In addition, participants came only from self-reported locations within the U.S. Trust in science differs from country to country (Cologna et al., 2025), so it is crucial to collect non-U.S. participant samples to examine whether these results replicate in other cultural and national contexts. This is especially important for establishing a foundational understanding of implicit trust in science and determining whether implicit-explicit trust patterns differ across countries, regions, and communities.

Relatedly, trust in science likely varies across geographic contexts in ways that reflect differences in institutional history, access to education and healthcare, urbanity/rurality, and political culture. Psychological research has expanded from the level of the individual to the level of regions, showing that regional psychological differences relate to meaningful predictors and outcomes (Calanchini et al., 2022; Rentfrow et al., 2008). Future research should examine whether implicit and explicit trust in science, and the discrepancy between them, differ regionally. For example, future research could examine whether people living in areas with fewer research institutions, less access to healthcare, or stronger political homogeneity show different implicit-explicit trust profiles than people living in more institutionally dense or politically diverse environments.

These questions are also connected to a broader puzzle about implicit measure stability. Implicit associations tend to have low test-retest reliability at the individual level, which Payne et al. (2017) argue is a reflection of situational context; the Bias of Crowds model conceptualizes implicit associations as person-by-situation interactions rather than stable individual traits. If implicit trust in science operates similarly, then regional and contextual variation becomes especially important: implicit trust in science may not be something a person simply has, but something that is activated, suppressed, or shaped by the environments people inhabit. Understanding how community-level factors, such as political culture, proximity to scientific institutions, access to healthcare, and institutional trust, aggregate to produce contextually situated implicit trust in science would be a theoretically rich future direction.

Measurement of Implicit Trust in Science

Another limitation concerns the measurement of implicit trust in science. The SC-IAT used here was an appropriate starting point for establishing implicit trust in science as a construct with behavioral validity. However, future research should explore multiple implicit measures, including priming tasks, approach-avoidance measures, and IATs using different comparison categories, to better characterize what implicit trust in science is and how it operates across contexts.

Although the unexpected negative relationship between implicit trust in science and science article selection raises questions about construct validity, several patterns suggest that the SC-IAT captured meaningful variance rather than noise. The SC-IAT reliability in the present studies (.77–.79) exceeded the typical range for this measure (.50–.70; Karpinski & Steinman, 2006), and the meta-analytic correlation between implicit and explicit trust in science fell within the .10–.30 range reported in the broader implicit-explicit literature. The cross-experiment variability in the implicit trust-behavior relationship suggests that this relationship may be sensitive to contextual factors rather than reflecting a simple measurement artifact. Future research should therefore continue refining implicit trust in science measures and examining the conditions under which implicit trust predicts behavior. For example, does motivation or opportunity to deliberate change the relationship between implicit trust, explicit trust, and behavior? Does it change the implicit-explicit discrepancy? These questions are crucial for understanding implicit trust in science as a construct.

Future research should also consider more rigorous methods for understanding the underlying cognitive processes reflected in implicit trust in science measures. Implicit measures are generally successful at reducing the influence of cognitive control processes reflected in traditional explicit measures, such as self-presentation motivations, but other forms of cognitive control still influence responses on implicit measures. For example, the IAT D-score is a summary statistic interpreted as a measure of association strength, but it may overlook the fact that IAT responses also reflect control-oriented executive functions such as task-set switching and working memory (Ito et al., 2015; Klauer et al., 2010). Summary statistics like the D-score are limited in their ability to distinguish among multiple cognitive processes when they jointly contribute to responses. Multinomial processing tree models (Riefer & Batchelder, 1988) offer an alternative approach by disentangling and quantifying the contributions of multiple processes to responses on tasks like the IAT. Applying a multinomial processing tree model to implicit trust in science responses could provide a stronger understanding of what is captured in an implicit trust measure and offer more insight into what implicit trust in science is and how it operates.

It would also be valuable to examine implicit trust in different facets of science, such as trust in science as an institution, trust in specific scientific domains such as medicine, climate science, or public health, and trust in scientists at different types of organizations. Informal observations and existing research suggest these may not be uniformly equivalent. People may trust climate science differently than pharmaceutical research, or university scientists differently than government scientists. Whether implicit and explicit trust in science are domain-general constructs or whether they fragment meaningfully across areas of science is a question the present design cannot answer.

Behavioral Outcomes and Ecological Validity

The science article selection task, while grounded in an established behavioral paradigm, is a relatively low-stakes proxy for real-world science engagement. Participants selected headlines without committing to read the articles, which may allow for impression management in ways that more consequential or private behavioral measures would not. Future research should examine whether the implicit-explicit dissociation in behavioral prediction replicates with other behaviors, particularly higher-stakes behaviors or behaviors where public visibility is manipulated.

Future work should also examine science article selection alongside other science-related behavioral outcomes to test whether the implicit-explicit behavioral dissociation generalizes beyond the experimental paradigm used here. These outcomes could include actual article reading time, willingness to share science information, policy support, health decision-making, misinformation correction, or engagement with scientific recommendations (e.g. recommended vaccine choices). Using multiple behavioral outcomes would help clarify whether implicit and explicit trust in science predict different kinds of science-related behavior.

Framing, Uncertainty, and Study Design

The framing and uncertainty manipulations consisted of a single brief exposure, therefore stronger or repeated manipulations may be necessary to produce reliable effects on explicit trust and behavior. Because of this limitation, the null behavioral findings should not be interpreted as evidence that framing can never affect science-related behavior. Future research should replicate and extend these experiments using stronger manipulations, repeated exposure designs, and more realistic scientific communication materials.

Relatedly, all three experiments used between-subjects designs, meaning that individual differences in baseline trust in science, political orientation, and scientific knowledge could not be controlled at the individual level. A within-subjects or longitudinal design measuring trust before and after exposure to framing and uncertainty manipulations would increase confidence in causal inferences about communication effects and improve sensitivity to detect individual-level change. Given the large role individual differences, such as political identity and science process skills, played in the present experiments, future research should use designs that can better estimate change within participants.

Future research using repeated-measures designs or natural experiments around real science communication events would also be valuable for establishing the magnitude and durability of framing effects at the individual level. These designs could examine whether dynamic framing effects persist over time, whether repeated exposure strengthens implicit trust in science, and whether uncertainty communication has different effects when people encounter it in real-world contexts.

Future research should also examine more realistic scientific framing and communication techniques related to trust in science. Some important questions include: How does the source of scientific information matter? Does the scientific topic or domain affect responses to framing? Does uncertainty coming from different sources, such as scientists, community leaders, government agencies, or media outlets, shape trust differently? These questions would help connect the present experimental findings to real-world science communication.

Science Domains, Sources, and Specificity

A related limitation concerns the domain specificity of the stimuli used in my dissertation. Specifically, the framing manipulation described cellular biology, and the uncertainty manipulation referenced unknown chemicals and health effects, but the explicit trust measures and the SC-IAT targeted trust in science and scientists broadly. While I did test multiple domains in the pre-test, ultimately I chose one. This lack of specificity means that these studies cannot determine whether framing and uncertainty effects differ across scientific domains or whether trust in science as an institution operates differently from trust in scientists as individuals.

Colloquially, when discussing my dissertation with people in my own life, this distinction seems to matter: people talk quite differently about their levels of trust in climate science versus pharmaceutical research, or in university scientists versus government scientists. Whether implicit and explicit trust in science are domain-general constructs or whether they fragment meaningfully across areas of science is a question the current experimental design cannot answer, but is important for future research to consider (I could do an entire second dissertation just on science versus scientists and domains!).

Individual Differences, Political Identity, and Social Context

Another important future direction concerns the role of political identity in driving the implicit-explicit discrepancy findings. These findings are theoretically rich and warrant further follow-up. It would be valuable to examine whether other individual difference variables, such as social dominance orientation, right-wing authoritarianism, racial identity, more specific religious identities (e.g. Christian Nationalism), or strength of political party identification explain additional variance in the discrepancy between implicit and explicit trust and its behavioral consequences.

These individual-level factors may explain meaningful variance in how people respond to framing and uncertainty, especially if baseline trust is controlled. Future work should also examine how communication strategies interact with political and social identity processes more directly. For example, dynamic framing may be received differently depending on whether it comes from a trusted or distrusted source, whether the scientific topic is politically relevant, or whether the message conflicts with group norms.

Science Process Skills and Scientific Literacy

The finding that science process skills moderated uncertainty effects in opposite directions for explicit trust and behavioral engagement points toward a broader research agenda examining how scientific literacy affects not only what people believe about science, but also how they emotionally and motivationally respond to uncertainty. Future research should employ different measures of scientific engagement and behavior to continue exploring this relationship.

It is also important for future research to investigate interventions aimed at increasing public understanding of the scientific process. The findings here suggest that science process skills may help buffer against the negative effects of uncertainty on explicit trust in science. However, more research is needed to determine whether improving people's understanding of scientific inquiry, evidence accumulation, and revision can lead to more resilient trust in science over time.

Exploratory Analyses and Statistical Power

Finally, several exploratory effects, such as the subscale findings and some of the discrepancy results, should be treated as hypothesis-generating rather than confirmatory given their exploratory nature and the number of comparisons involved. In addition, all three experiments were slightly underpowered relative to original targets due to higher-than-anticipated exclusion rates, which may have contributed to some inconsistency across experiments, particularly in the framing effects. Future research should use larger samples to provide more stable estimates of the effects observed here and to test whether the exploratory patterns replicate.

Broader Theoretical Extensions

Some of the results from my dissertation also point to broader theoretical extensions beyond the trust in science literature. The general trust literature lacks a robust understanding of implicit trust, making this a rich and understudied area for future research. Some studies have examined implicit and explicit trust in domains such as safety and government, but trust in relationships, trust in strangers, institutional trust, and general trust tendencies should also be considered at both the implicit and explicit level.

Future research could examine whether some domains of trust operate similarly to traditional evaluations or whether different domains of trust show distinct implicit-explicit patterns.

Furthermore, the dynamic norms literature has primarily focused on explicit outcomes. The results across Experiments 2 and 3 suggest that examining dynamic norm framing effects on implicit trust is a promising and largely unexplored direction. Future work could examine whether dynamic framing shifts implicit trust in other domains and whether such shifts depend on the type of target, the strength of prior associations, or the presence of uncertainty. Together, all of these limitations and future directions highlight the need for continued research exploring implicit and explicit trust in science to better understand how trust in science develops, changes, and translates into real-world behavior.

Conclusion

In a world where people trust astrology more than astronomy, influencers more than immunologists, and conspiracy theories more than climate science, my dissertation offers a novel and nuanced picture of public trust in science. Across three experiments, the findings demonstrate that implicit and explicit trust in science reflect distinct cognitive evaluation processes shaped by communication framing, interpretations of uncertainty, understanding of the scientific process, and broader social identities.

The present findings suggest that implicit and explicit trust in science measures capture different aspects of how people trust science and scientists. Implicit and explicit trust in science do not always align with one another and do not always predict behavior in the same way. The findings also demonstrate that framing science as dynamic and evolving can strengthen trust in science without necessarily undermining credibility. Furthermore, understanding science as a process appears to shape how individuals interpret scientific uncertainty, with stronger science process skills buffering against some of the potentially negative effects of uncertainty.

In addition, the results suggest that people's implicit trust in science may be less negative than their explicit reports suggest, at least in the present samples. Although political and religious differences emerged consistently for explicit trust in science, these same differences were weaker or absent for implicit trust in science. This pattern offers a cautious glimmer of hope: people who explicitly report lower trust in science may not necessarily have equally negative automatic associations with science. Instead, some expressions of distrust may reflect political, religious, and social pressures that shape what people feel comfortable reporting about science. In other words, people's distrust in science may sometimes function as an identity signal more than a direct reflection of people's implicit associations between science and trustworthiness. This distinction matters greatly for science communication. Efforts to shift explicit trust may need to address the political, social, and identity-based contexts that shape what people report about science, whereas efforts to strengthen implicit trust may benefit from repeated communication that frames science as dynamic, transparent, and self-correcting. The gap between implicit and explicit trust in science therefore has real consequences for public health, science policy, and society more broadly.

None of this offers an easy answer to the question of how to rebuild public trust in science. But it does suggest that the problem is more complicated, and maybe more hopeful, than it first appears. The challenge may not be to build trust from nothing, but to understand when, why, and for whom trust in science becomes suppressed, politicized, or disconnected from behavior. Rebuilding trust in science will require more than giving people more facts; it will require interventions and communication strategies that account for context and helping people understand why science changes, why uncertainty is part of the process, and why self-correction is not a failure of science but the very reason science can be trusted. My dissertation brings us closer to a more complete understanding of trust in science, so that we can better shape and rebuild the public's trust in science.

References

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179-211. https://doi.org/10.1016/0749-5978(91)90020-T

Ajzen, I., & Fishbein, M. (1980). *Understanding attitudes and predicting social behavior.* Prentice-Hall.

Ballard, T., & Lewandowsky, S. (2015). When, not if: The inescapability of an uncertain climate future. *Philosophical Transactions, 373*(2055), 20140464. https://doi.org/10.1098/rsta.2014.0464

Besley, J. C., & Tiffany, L. A. (2023). What are you assessing when you measure "trust" in scientists with a direct measure? *Public Understanding of Science*, *32*(6), 709-726. https://doi.org/10.1177/09636625231161302

Bicchieri, C., Fatas, E., Aldama, A., Casas, A., Deshpande, I., Lauro, M., Parilli, C., Spohn, M., Pereira, P. & Wen, R. (2021). In science we (should) trust: Expectations and compliance across nine countries during the COVID-19 pandemic. *PloS One, 16*(6), 1-17. https://doi.org/10.1371/journal.pone.0252892

Borinca, I., Griffin, S. M., McMahon, G., Maher, P., & Muldoon, O. T. (2024). Nudging (dis) trust in science: Exploring the interplay of social norms and scientific trust during public health crises. *Journal of Applied Social Psychology*, *54*(8), 487-504. https://doi.org/10.1111/jasp.13053

Bou Malham, P., & Saucier, G. (2016). The conceptual link between social desirability and cultural normativity. *International Journal of Psychology, 51*(6), 474-480. https://doi.org/10.1002/ijop.12261

Briñol, P., Petty, R. E., & Wheeler, S. C. (2006). Discrepancies between explicit and implicit self-concepts: Consequences for information processing. *Journal of Personality and Social Psychology, 91*(1), 154-170. https://doi.org/10.1037/0022-3514.91.1.154

Bromme, R., Mede, N. G., Thomm, E., Kremer, B., & Ziegler, R. (2022). An anchor in troubled times: Trust in science before and within the COVID-19 pandemic. *PloS One, 17*(2), 1-27. https://doi.org/10.1371/journal.pone.0262823

Budescu, D. V., Broomell, S., & Por, H.-H. (2009). Improving communication of uncertainty in the reports of the intergovernmental panel on climate change. *Psychological Science*, *20*(3), 299-308. https://doi.org/10.1111/j.1467-9280.2009.02284.x

Burns, C., Mearns, K., & McGeorge, P. (2006). Explicit and implicit trust within safety culture. *Risk Analysis: An Official Publication of the Society for Risk Analysis*, *26*(5), 1139-1150. https://doi.org/10.1111/j.1539-6924.2006.00821.x

Calanchini, J., Hehman, E., Ebert, T., Esposito, E., Simon, D., & Wilson, L. (2022). Regional intergroup bias. *Advances in Experimental Social Psychology, 66*, 281-328. 10.31234/osf.io/gh9vj

Čavojová, V., Šrol, J., & Ballová Mikušková, E. (2023). Scientific reasoning is associated with rejection of unfounded health beliefs and adherence to evidence-based regulations during the Covid-19 pandemic. *Current Psychology*, *43*, 8288-8302. https://doi.org/10.1007/s12144-023-04284-y

Chaiken, S., & Trope, Y. (Eds.). (1999). *Dual-process theories in social psychology.* The Guilford Press.

Coelho, G.L.D.H., Hanel, P.H.P, & Wolf, L.J. (2018). The very efficient assessment of need for cognition: Developing a six-item version. *Assessment, Online First, 27*(8) 1-16. https://doi.org/10.1177/1073191118793208

Cologna, V., Mede, N.G., Berger, S. et al. (2025). Trust in scientists and their role in society across 68 countries. Nature Human Behavior, *9*, 713-730. https://doi.org/10.1038/s41562-024-02090-5

Corbett, J. B., & Durfee, J. L. (2004). Testing public (un)certainty of science: Media representations of global warming. *Science Communication*, *26*(2), 129-151. https://doi.org/10.1177/1075547004270234

Covitt, B. A., & Anderson, C. W. (2022). Untangling trustworthiness and uncertainty in science: Implications for science education: Implications for science education. *Science & Education*, *31*(5), 1155-1180. https://doi.org/10.1007/s11191-022-00322-6

DiMaggio, P., Sotoudeh, R., Goldberg, A., and Shepherd, H. (2018) Culture out of attitudes: Relationality, population heterogeneity and attitudes toward science and religion in the U.S. Poetics, 68, 31-51. https://doi.org/10.1016/j.poetic.2017.11.001.

Faul, F., Erdfelder, E., Lang, A. G., & Buchner, A. (2007). G* Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods, 39*(2), 175-191. https://doi.org/10.3758/BF03193146

Fazeli, S., Loni, B., Bellogin, A., Drachsler, H., & Sloep, P. (2014, October). Implicit vs. explicit trust in social matrix factorization. In *Proceedings of the 8th ACM Conference on Recommender systems* (pp. 317-320).

Fazio, R. H. (1990). Multiple processes by which attitudes guide behavior: The MODE model as an integrative framework. In *Advances in experimental social psychology* (Vol. 23, pp. 75-109). Academic Press.

Fazio, R. H., & Olson, M. A. (2003). Implicit measures in social cognition research: Their meaning and use. *Annual Review of Psychology*, *54*(1), 297-327. https://doi.org/10.1146/annurev.psych.54.101601.145225

Fazio, R. H., & Olson, M. A. (2014). The MODE model: Attitude-behavior processes as a function of motivation and opportunity. In J. W. Sherman, B. Gawronski, & Y. Trope (Eds.), *Dual-process theories of the social mind* (pp. 155-171). The Guilford Press.

Fisher, R. J. (1993). Social desirability bias and the validity of indirect questioning. *Journal of Consumer Research, 20*(2), 303-315. https://doi.org/10.1086/209351

Furnham, A. (1986). Response bias, social desirability and dissimulation. *Personality and Individual Differences, 7*(3), 385-400. https://doi.org/10.1016/0191-8869(86)90014-0

Gawronski, B., & Bodenhausen, G. V. (2006). Associative and propositional processes in evaluation: an integrative review of implicit and explicit attitude change. *Psychological Bulletin, 132*(5), 692. 10.1037/0033-2909.132.5.692

Gawronski, B., & Bodenhausen, G. V. (2009). Operating principles versus operating conditions in the distinction between associative and propositional processes. *The Behavioral and Brain Sciences*, *32*(2), 207-208. https://doi.org/10.1017/s0140525x09000958

Gawronski, B., & Creighton, L. A. (2013). Dual process theories. In D. E. Carlston (Ed.), *The Oxford handbook of social cognition* (pp. 282-312). Oxford University Press. https://doi.org/10.1093/OXFORDHB/9780199730018.013.0014

Grand, A., Wilkinson, C., Bultitude, K., & Winfield, A. F. T. (2012). Open science: A new "trust technology"? *Science Communication, 34*(5), 679-689. https://doi.org/10.1177/1075547012443021

Greenwald, A. G., & Farnham, S. D. (2000). Using the Implicit Association Test to measure self-esteem and self-concept. Journal of Personality and Social Psychology, 79(6), 1022-1038. https://doi.org/10.1037/0022-3514.79.6.1022

Greenwald, A. G., McGhee, D. E., & Schwartz, J. L. K. (1998). Measuring individual differences in implicit cognition: The implicit association test. *Journal of Personality and Social Psychology, 74*(6), 1464-1480. https://doi.org/10.1037/0022-3514.74.6.1464

Greenwald, A. G., Nosek, B. A., & Banaji, M. R. (2003). "Understanding and using the Implicit Association Test: I. An improved scoring algorithm": Correction to Greenwald et al. (2003). *Journal of Personality and Social Psychology, 85*(3), 481. https://doi.org/10.1037/h0087889

Greenwald, A. G., Poehlman, T. A., Uhlmann, E. L., & Banaji, M. R. (2009). Understanding and using the Implicit Association Test: III. Meta-analysis of predictive validity. *Journal of Personality and Social Psychology, 97*(1), 17-41. https://doi.org/10.1037/a0015575

Guidotti, T. L. (2017). Trust, contingent thinking, and the moral posture of science. *Archives of Environmental & Occupational Health*, *72*(2), 61-62. https://doi.org/10.1080/19338244.2017.1287481

Guo, G., Zhang, J., & Yorke-Smith, N. (2014). Leveraging multiviews of trust and similarity to enhance clustering-based recommender systems. *Knowledge-Based Systems, 74*, 14-27. https://doi.org/10.1145/2554850.2554878

Gustafson, A., & Rice, R. E. (2020). A review of the effects of uncertainty in public science communication. *Public Understanding of Science, 29*(6), 614-633. https://doi.org/10.1177/0963662520942122

Hall, M. A., Dugan, E., Zheng, B., & Mishra, A. K. (2001). Trust in physicians and medical institutions: what is it, can it be measured, and does it matter?. *The Milbank Quarterly, 79*(4), 613-639. https://doi.org/10.1111/1468-0009.00223

Hatton, C. R., Barry, C. L., Levine, A. S., McGinty, E. E., & Han, H. (2022). American trust in science & institutions in the time of COVID-19. *Daedalus, 151*(4), 83-97. https://doi.org/10.1162/daed_a_01945

Hendriks F., Jucks R. (2020). Does scientific uncertainty in news articles affect readers' trust and decision-making? *Media and Communication, 8*(2), 401-412. https://doi.org/10.17645/mac.v8i2.2824

Hertzberg, L. (1988). On the attitude of trust. *Inquiry (Oslo, Norway)*, *31*(3), 307-322. https://doi.org/10.1080/00201748808602157

Hofmann, W., Gawronski, B., Gschwendner, T., Le, H., & Schmitt, M. (2005). A meta-analysis on the correlation between the implicit association test and explicit self-report measures. *Personality & Social Psychology Bulletin*, *31*(10), 1369-1385. https://doi.org/10.1177/0146167205275613

Hofmann, W., Gschwendner, T., Friese, M., Wiers, R. W., & Schmitt, M. (2008). Working memory capacity and self-regulatory behavior: Toward an individual differences perspective on behavior determination by automatic versus controlled processes. *Journal of Personality and Social Psychology*, *95*(4), 962-977. https://doi.org/10.1037/a0012705

Intawan, C., & Nicholson, S. P. (2018). My trust in government is implicit: Automatic trust in government and system support. *The Journal of Politics, 80*(2), 601-614. https://doi.org/10.1086/694785

Intemann, K. (2023). Science communication and public trust in science. *Interdisciplinary Science Reviews*, *48*(2), 350-365. https://doi.org/10.1080/03080188.2022.2152244

Iordanou, K., Antoniou, A. & De Vos, M. (2026). Public trust in science: A systematic literature review. *Journal of Academic Ethics, 24*, 56. https://doi.org/10.1007/s10805-026-09732-5

Irwin, A., & Horst, M. (2016). Communicating trust and trusting science communication-some critical remarks. *Journal of Science Communication, 15*(6), 1-5. https://doi.org/10.22323/2.15060101

Jagd, S., & Fuglsang, L. (2016). Trust as process within and between organizations: discussion and emerging themes. In *Trust, organizations and social interaction* (pp. 327-332). Edward Elgar Publishing. https://doi.org/10.4337/9781783476206.00027

Jamieson, K. H. (2017). The need for a science of science communication: Communicating science's values and norms. In D. A. Scheufele, K. H. Jamieson, & D. M. Kahan (Eds.), *The Oxford Handbook of the Science of Science Communication*. Oxford University Press. https://doi.org/10.1093/oxfordhb/9780190497620.013.2

Jones, A. J. I. (2002). On the concept of trust. *Decision Support Systems*, *33*, 225-232. https://doi.org/10.1016/S0167-9236(02)00013-1

Karpinski, A., & Steinman, R. B. (2006). The single category implicit association test as a measure of implicit social cognition. *Journal of Personality and Social Psychology, 91*(1), 16-32. https://doi.org/10.1037/0022-3514.91.1.16

Kennedy, B. & Tyson, A. (2023, November 14). *Americans' trust in scientists, positive views of science continue to decline.* Pew Research Center. https://www.pewresearch.org/science/2023/11/14/americans-trust-in-scientists-positive-views-of-science-continue-to-decline/

Knobloch-Westerwick, S., & Meng, J. (2009). Looking the other way: Selective exposure to attitude-consistent and counterattitudinal political information. *Communication Research, 36*(3), 426-448. https://doi.org/10.1177/0093650209333030

Kreps, S. E., & Kriner, D. L. (2020). Model uncertainty, political contestation, and public trust in science: Evidence from the COVID-19 pandemic. *Science Advances*, *6*(43), 1-12. https://doi.org/10.1126/sciadv.abd4563

Krumpal, I., & Voss, T. (2020). Sensitive questions and trust: Explaining respondents' behavior in randomized response surveys. *SAGE Open, 10*(3) 1-17. https://doi.org/10.1177/2158244020936223

Lee, S., Jones-Jang, S. M., Chung, M., Lee, E. W. J., & Diehl, T. (2023). Examining the role of distrust in science and social media use: Effects on susceptibility to COVID misperceptions with panel data. *Mass Communication and Society*, *27*(4), 653-678. https://doi.org/10.1080/15205436.2023.2268053

Luhmann, N. (1979) *Trust and Power*. Wiley, Chichester.

Ma, H., & Reynolds-Tylus, T. (2024). Dynamic norms and vaping: A test of four mediators. *Substance Use & Misuse*, *59*(14), 2037-2046. https://doi.org/10.1080/10826084.2024.2392535

Mayo, R. (2015). Cognition is a matter of trust: Distrust tunes cognitive processes. *European Review of Social Psychology*, *26*(1), 283-327. https://doi.org/10.1080/10463283.2015.1117249

Merritt, S. M., Heimbaugh, H., LaChapell, J., & Lee, D. (2013). I trust it, but I don't know why: Effects of implicit attitudes toward automation on trust in an automated system. *Human Factors, 55*(3), 520-534. https://doi.org/10.1177/0018720812465081

Millar, R., & Wynne, B. (1988). Public understanding of science: From contents to processes. *International Journal of Science Education*, *10*(4), 388-398. https://doi.org/10.1080/0950069880100406

Nosek, B. A. (2007). Implicit-explicit relations. *Current Directions in Psychological Science, 16*(2), 65-69. https://doi.org/10.1111/j.1467-8721.2007.00477.x

Nosek, B. A., Banaji, M. R., & Greenwald, A. G. (2002). Harvesting implicit group attitudes and beliefs from a demonstration web site. *Group Dynamics: Theory, Research, and Practice, 6*(1), 101-115. https://doi.org/10.1037/1089-2699.6.1.101

O'Brien, T. L., & Noy, S. (2025). Religion, perceptions of scientists' moral culture, and support for science in the United States. *American Sociological Review, 90*(2), 257-290. https://doi.org/10.1177/00031224251316904

O'Shea, B. (2018). Can implicit measures contribute to a true understanding of people's attitudes and stereotypes?. *Exchanges: The Interdisciplinary Research Journal, 5*(2), 106-131. https://doi.org/10.31273/eirj.v5i2.233

Panek, E. (2016). High-choice revisited: An experimental analysis of the dynamics of news selection behavior in high-choice media environments. *Journalism & Mass Communication Quarterly, 93*(4), 836-856. https://doi.org/10.1177/1077699016630251

Phillips, J. E., & Olson, M. A. (2014). When implicitly and explicitly measured racial attitudes align: The roles of social desirability and thoughtful responding. *Basic and Applied Social Psychology, 36*(2), 125-132. https://doi.org/10.1080/01973533.2014.881287

Plohl, N., & Musil, B. (2023). Trust in science moderates the effects of high/low threat communication on psychological reactance to COVID-19-related public health messages. *Journal of Communication in Healthcare*, *16*(4), 401-411. https://doi.org/10.1080/17538068.2023.2279395

Rabinovich, A., Morton, T. A., & Birney, M. E. (2012). Communicating climate science: The role of perceived communicator's motives. *Journal of Environmental Psychology, 32*(1), 11-18. https://doi.org/10.1016/j.jenvp.2011.09.002

Rammstedt, B., & John, O. P. (2007). Measuring personality in one minute or less: A 10-item short version of the Big Five Inventory in English and German. *Journal of Research in Personality, 41*(1), 203-212. https://doi.org/10.1016/j.jrp.2006.02.001

Rentfrow, P. J., Gosling, S. D., & Potter, J. (2008). A theory of the emergence, persistence, and expression of geographic variation in psychological characteristics. *Perspectives on Psychological Science, 3*(5), 339-369. https://doi.org/10.1111/j.1745-6924.2008.00084.x

Rosman, T., & Grösser, S. (2023). Belief updating when confronted with scientific evidence: Examining the role of trust in science. *Public Understanding of Science, 33*(3), 308-324. https://doi.org/10.1177/09636625231203538

Rydell, R. J., McConnell, A. R., Mackie, D. M., & Strain, L. M. (2006). Of two minds: Forming and changing valence-inconsistent implicit and explicit attitudes. *Psychological Science, 17*(11), 954-958. https://doi.org/10.1111/j.1467-9280.2006.01811.x

Scheitle, C. P., Corcoran, K. E., & DiGregorio, B. D. (2025). Questions of truth vs. questions of trust: Nuancing the influences of religiosity, political conservatism, and Christian nationalism on attitudes towards science. *Religions*, *16*(7), 935. https://doi.org/10.3390/rel16070935

Schnabel, K., Banse, R., & Asendorpf, J. (2006). Employing automatic approach and avoidance tendencies for the assessment of implicit personality self-concept: The Implicit Association Procedure (IAP). *Experimental Psychology, 53*(1), 69-76. https://doi.org/10.1027/1618-3169.53.1.69

Schoor, C., & Schütz, A. (2021). Science-utility and science-trust associations and how they relate to knowledge about how science works. *PloS One*, *16*(12), 1-21. https://doi.org/10.1371/journal.pone.0260586

Sinatra, G. M., & Hofer, B. K. (2016). Public understanding of science: Policy and educational implications. *Policy Insights from the Behavioral and Brain Sciences, 3*(2), 245-253. https://doi.org/10.1177/2372732216656870

Slater, M. H., Huxster, J. K., & Bresticker, J. E. (2019). Understanding and trusting science. *Journal for General Philosophy of Science, 50,* 247-261. https://doi.org/10.1007/s10838-019-09447-9

Smith, E. R., & Collins, E. C. (2009). Dual-process models: A social psychological perspective. In *In two minds: Dual processes and beyond* (pp. 197-216). Oxford University PressOxford. https://doi.org/10.1093/acprof:oso/9780199230167.003.0009

Sotério, C. (2021). The provisional nature of science evidenced in times of pandemic. *Alternautas, 8*(1). https://doi.org/10.31273/alternautas.v8i1.1121

Sparkman, G., & Walton, G. M. (2017). Dynamic norms promote sustainable behavior, even if it is counternormative. *Psychological Science*, *28*(11), 1663-1674. https://doi.org/10.1177/0956797617719950

Steijaert, M. J., Schaap, G., & Riet, J. V. T. (2020). Two-sided science: Communicating scientific uncertainty increases trust in scientists and donation intention by decreasing attribution of communicator bias. *Communications, 46*(2), 297-316. https://doi.org/10.1515/commun-2019-0123

Sturgis, P., Brunton-Smith, I., & Jackson, J. (2021). Trust in science, social consensus and vaccine confidence. *Nature Human Behaviour, 5*(11), 1528-1534. https://doi.org/10.1038/s41562-021-01115-7

Sztompka, P. (2007). Trust in science: Robert K. Merton's inspirations. *Journal of Classical Sociology*, *7*(2), 211-220. https://doi.org/10.1177/1468795x07078038

Todorov, A., Pakrashi, M., & Oosterhof, N. N. (2009). Evaluating faces on trustworthiness after minimal time exposure. *Social Cognition, 27*(6), 813-833. https://doi.org/10.1521/soco.2009.27.6.813

van der Bles, A. M., van der Linden, S., Freeman, A. L., & Spiegelhalter, D. J. (2020). The effects of communicating uncertainty on public trust in facts and numbers. *Proceedings of the National Academy of Sciences, 117*(14), 7672-7683. https://doi.org/10.1073/pnas.1913678117

Voas, D. (2014). Towards a sociology of attitudes. *Sociological Research Online, 19*(1), 132-144. https://doi.org/10.5153/sro.3289

Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: the PANAS scales. *Journal of Personality and Social Psychology, 54*(6), 1063. https://doi.org/10.1037/0022-3514.54.6.1063

Wei, Z., Zhao, Z., & Zheng, Y. (2019). Following the majority: Social influence in trusting behavior. *Frontiers in Neuroscience, 13*(89), 1-8. https://doi.org/10.3389/fnins.2019.00089

Windsor-Shellard, B., & Haddock, G. (2014). On feeling torn about one's sexuality: The effects of explicit-implicit sexual orientation ambivalence: *Personality and Social Psychology Bulletin, 40*(9), 1215-1228. https://doi.org/10.1177/0146167214539018

Wisniewski, K., Ting, C., & Matzen, L. (2024). Trust us: A simple model for understanding appropriate trust in AI. *AHFE International*, *159,* 1-11. https://doi.org/10.54941/ahfe1005594

Yadav, A., Chakraverty, S., & Sibal, R. (2015, October). A survey of implicit trust on social networks. In *2015 International Conference on Green Computing and Internet of Things (ICGCIoT)* (pp. 1511-1515). Institute of Electrical and Electronics Engineers.