Perceived self and social relevance of content motivates news sharing across cultures and topics

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Abstract

Well-informed individual and collective decision-making is aided by access to high-quality, factual information. What motivates people to share high-quality news and how can these motives be leveraged to promote news sharing? Based on the theory that self-related and social motives encourage sharing behavior, we designed and tested interventions to increase news sharing. In the interventions, individuals were exposed to actual news stories and were prompted to identify why the content was relevant to themselves (self-relevance) or people they know (social relevance). Across four studies ($N_{participants}$ = 2,559, $N_{observations}$ = 18,780), we systematically examined the effectiveness of these interventions, their generalizability across news topics (climate change and health) and cultures (the United States of America and the Netherlands), their translation to more naturalistic contexts, and their underlying neuropsychological mechanisms. In all studies, we observed expected positive correlations among perceived self and social relevance and sharing intentions. In a neuroimaging study, we also observed corresponding increases in activity in self-referential and social cognitive brain regions. Using the content-framing interventions to test causal relationships, we found that the interventions increased sharing intentions and behavior. Furthermore, we observed generalizability across news topics and cultural contexts and translation to an ecologically valid news exposure context. These findings advance theory by adding neural and behavioral evidence that self-related and social motives prompt people to share information, and demonstrate the ability of content-framing interventions to harness these motives to encourage high-quality news sharing.

Significance statement

The information people are exposed to shapes their attitudes, beliefs, and behavior. Thus, the quality of the information being shared in social networks has important implications for the health and well-being of individuals and societies. Given the detrimental effects of low-quality (false, inaccurate, or misleading) information, it is important to understand what makes accurate, high-quality information spread. Using neural and behavioral experiments, we identify key mechanisms that motivate people to share high-quality news and leverage them to design easily scalable interventions that work in real online environments, for different types of content, and across different populations. Overall, our findings help explain why people decide to share and how to more effectively design interventions to promote sharing of high-quality information.

The ability of individuals to make well-informed decisions and work together effectively towards prosocial goals, like combating climate change or supporting community health, depends in part on access to high-quality, accurate information. Indeed, the abundance of low-quality information that contains false, inaccurate, or misleading claims circulating on social media presents a serious threat to public health and societal functioning (Kirk Sell et al., 2021; Office of the United States Surgeon General, 2021; United States Department of Homeland Security, 2020; World Health Organization, 2020). Given that people are increasingly using social media to receive news and information (Pew Research Center, 2023), it is critical to understand how to increase the quality of information that is transmitted through social networks. Recent research has identified several promising interventions to decrease the spread of low-quality information (Ceylan et al., 2023; Guess et al., 2020; Pennycook & Rand, 2022; Roozenbeek et al., 2022). Another approach to raising the overall quality of the information available is to increase sharing of high-quality information. However, scalable, evidence-based interventions with this goal have not yet been developed. Our work aims to fill this gap by developing theory-based interventions that promote the sharing of high-quality news about societally-relevant topics, such as health and climate change.

These interventions are rooted in the value-based framework of sharing, which theorizes that sharing is a value-based decision in which people implicitly and explicitly weigh the costs and benefits of sharing and are more likely to share content if they expect it to lead to positive outcomes (Scholz, Jovanova, et al., 2020; Scholz & Falk, 2020). Because people tend to assign positive value to their self-concepts (Beer & Hughes, 2010; Chavez et al., 2016; Pfeifer & Berkman, 2018) and to holding positive relations with others (Allen et al., 2021; Baumeister & Leary, 1995; Deci & Ryan, 2000; Ryff, 1995), the self-related and social motives are expected to influence how valuable the act of sharing will be. Empirically, when people perceive information as more relevant to themselves (self-relevance) and to others (social relevance), or consider how it might help them connect with others, they are more motivated to share (Barasch & Berger, 2014; Berger, 2014a; Cosme et al., 2022; Scholz et al., 2023). In addition, when messages evoke greater activity in brain regions associated with self-referential processing, social cognition, and valuation, they are more likely to be shared at scale (Chan et al., 2023; Motoki et al., 2020; Scholz et al., 2017; Scholz, Baek, et al., 2020). Thus, the self and social relevance of information are two potential intervention targets to promote the sharing of high-quality news. In prior work, we designed content-framing interventions targeting self and social relevance and found initial evidence that they increased intentions to share high-quality news articles about climate change and COVID-19 (Cosme et al., 2022).

Current research

The present research systematically tests these interventions' 1) effectiveness, 2) generalizability across news topics and cultural contexts, 3) translation to naturalistic online environments, 3) neuropsychological mechanisms, and 4) downstream influences on attitudes and behavior. We adopt a multi-method approach using large-scale online experimental techniques, an online field study, and cross-cultural functional magnetic resonance imaging (fMRI) to achieve these goals across four studies ($N_{participants}$ = 2,559, $N_{observations}$ = 18,780; Table 1).

Table 1
Overview of studies

Study	N	Study design	Intervention design	Topic	Self & social motive DVs	Sharing DVs
1*	1613	Online experiment	Between-person	Climate	Self & social relevance	Broad- and narrowcast intentions
2	448	Online field experiment	Within-person	Climate & health	Self & social relevance	Broad- and narrowcast intentions & behavior
3*	85	Cross-cultural fMRI experiment	Within-person	Climate & health	Self & social relevance, Self & social ROIs	Narrowcast intentions
4	413	Online experiment	Mixed	Climate & health	Self & social relevance	Broad- and narrowcast intentions

Note. *Study preregistered prior to data collection; DVs = dependent variables; ROIs = brain regions of interest; Broadcast intention = intention to share with a large audience on social media; Narrowcast intention = intention to share directly with someone (e.g. via email or direct message).

Study 1 extends the initial within-person intervention (Cosme et al., 2022) to test its ability to increase climate news sharing among individuals who are exposed to a single intervention condition and also measures potential downstream intervention-related effects on climate-related beliefs, attitudes, and behavior. Participants were randomly assigned to a “self-focused” intervention group targeting self-relevance, an “other-focused” intervention group targeting social relevance, or a no-intervention control group (Figure 1), and completed an online survey. All participants were exposed to news headlines and ledes and rated how self and socially relevant they found each article, and their intentions to share the articles on social media and directly with people (e.g., via email or direct message). Participants in the self- and other-focused interventions also wrote brief comments for each article as if they were posting on social media describing why each article was relevant to themselves (self-focused) or people they know (other-focused). Preregistered analyses (https://osf.io/7by85) tested the degree to which the self- and other-focused interventions causally increased the perceived relevance of climate news and intentions to share, as well as correlational relationships between relevance and sharing across the groups. Exploratory analyses also assessed the impact of the interventions on perceived climate knowledge, self-efficacy, climate petition sharing, and perceived impact of individual climate actions, such as driving less and eating less meat, and collective climate actions, such as contacting representatives, donating, and volunteering.

Study 2 extended these findings to a more ecologically valid context via an online field study. Rather than being exposed to headlines and ledes in an online survey, participants were presented with entire news articles using a browser plugin on a platform that resembled how they might encounter news content naturally online and allowed them to actually share the articles. To maximize power, this study was conducted using a within-person design; participants experienced both content-framing interventions, as well as an active control in which they wrote comments describing what the article was about. In addition to news articles about climate change, participants also viewed articles about general health topics. Participants rated the articles on the same dimensions as in Study 1 and also had the opportunity to share them on Facebook, Reddit, LinkedIn, Twitter, or via email. We extended the analyses in Study 1 to examine relationships with sharing behavior and explore potential differences between climate and health news.

Study 3 used fMRI to test the neuropsychological mechanisms underlying sharing decisions across two Western cultures. American and Dutch participants completed a similar within-person content-framing intervention as in Study 2 but due to the limitations of the MRI environment, they only reflected on the intervention prompts rather than writing comments in response to them. In preregistered analyses (https://osf.io/2d35g), we tested correlational and causal relationships among perceived self and social relevance, activity in brain regions associated with self-referential processing and social cognition, and intentions to share the news articles. We also examined whether these self-reported and brain indices explained unique variance in news sharing intentions, and explored the degree to which these relationships differed across cultures and news topics.

Because we found that the content-framing interventions were less effective when participants merely reflected on the self and social relevance of news articles in Study 3, Study 4 examined how different factors affecting engagement (reflecting or writing comments, and the amount of reflection time allowed) impacted intervention effectiveness. Specifically, Study 4 used the same within-person designs in Studies 2-3, but included an additional between-person manipulation of the type of reflection (writing comments or reflecting only) and amount of time allocated (12s versus unlimited time).

Hypotheses

H1. Greater (a) self-relevance and (b) social relevance ratings will be associated with stronger news sharing intentions and behavior.

H2. Compared to the control condition, the (a) self-focused condition will increase self-relevance ratings, and (b) other-focused condition will increase social relevance ratings.

H3. Compared to the control condition, the (a) self-focused and (b) other-focused conditions will increase news sharing intentions and behavior.

H4. Greater activity in the (a) self-referential region of interest (ROI) will be associated with higher self-relevance ratings, and (b) greater activity in the social cognitive ROI will be associated with higher social relevance ratings.

H5. Greater activity in the (a) self-referential and (b) social cognitive ROIs will be associated with stronger news sharing intentions.

H6. Compared to the control condition, the (a) self-focused condition will increase activity in the self-referential ROI, and the (b) other-focused condition will increase activity in the social cognitive ROI.

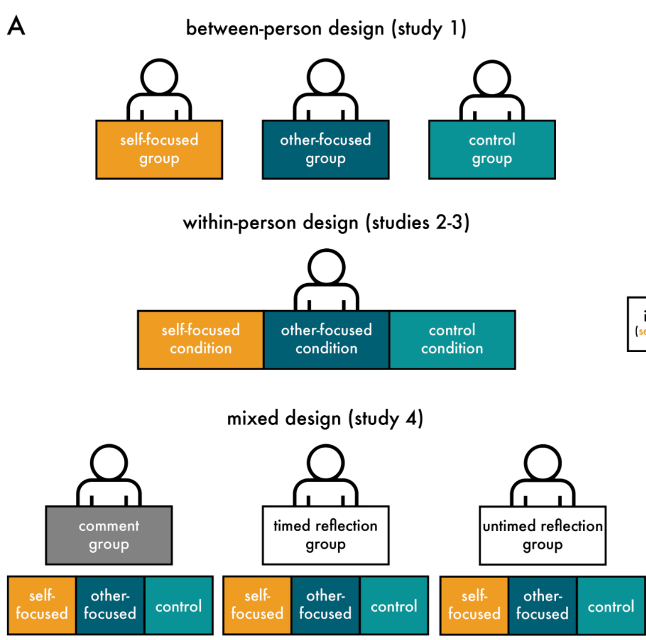

Figure 1. Study experimental design and conceptual model outlining hypotheses. (A) Study 1 used a between-person design in which participants were randomly assigned to either the self- or other-focused intervention groups or a control group that completed no intervention. Studies 2-3 used within-person

designs in which participants experienced all intervention conditions. Study 4 used the same design as Studies 2-3 but included an additional between-person manipulation of the type of reflection (writing comments or reflecting only) and amount of time allocated (12s versus unlimited time). (B) Perceived relevance and brain activity in ROIs are expected to be positively correlated (H4a-b) and each of these indicators of self and social motives are expected to be positively correlated with news sharing intentions and/or behavior (H1a-b, H5a-b). Relative to a control, the content-framing interventions are expected to increase each of the self and social motive indicators (H2a-b, H6a-b) and news sharing intentions and/or behavior (H3).

Results

H1: Self and social relevance are positively correlated with news sharing

First, we sought to replicate prior findings indicating that perceptions of the self and social relevance of information are positively correlated with intentions to share (Cosme et al., 2022). Across all studies, we found convergent evidence that when participants perceived news articles as more self and socially relevant, they also reported stronger intentions to share the articles (Table 2, Figure 2). Joint estimates across studies for the relationship between self-relevance and sharing are as follows: β = 0.23, 95% CI [0.21, 0.25], t(905.59) = 20.28, p < .001 for broadcast sharing and β = 0.19, 95% CI [0.17, 0.22], t(753.60) = 16.51, p < .001 for narrowcast sharing. Joint estimates across studies for the relationship between social relevance and sharing are as follows: β = 0.21, 95% CI [0.19, 0.23], t(948.80) = 18.40, p < .001 for broadcast sharing and β = 0.36, 95% CI [0.33, 0.38], t(858.57) = 29.35, p < .001 for narrowcast sharing. Furthermore, in the Study 2 field experiment, greater perceived social relevance, but not self-relevance, was associated with an increased likelihood of actual sharing behavior.

Table 2
Results from models testing hypotheses H1-3

Dependent variable	Parameter	β [95% CI]			
		Study 1	Study 2	Study 3	Study 4
H1a-b: Broadcast sharing intention	self-relevance	0.26 [0.23, 0.29]	0.22 [0.19, 0.26]	—	0.15 [0.10, 0.19]
	social relevance	0.21 [0.18, 0.24]	0.23 [0.20, 0.26]	—	0.20 [0.15, 0.24]
H1a-b: Narrowcast sharing intention	self-relevance	0.25 [0.21, 0.28]	0.08 [0.04, 0.11]	0.29 [0.26, 0.33]	0.05 [0.00, 0.10]
	social relevance	0.31 [0.28, 0.35]	0.37 [0.33, 0.40]	0.22 [0.17, 0.26]	0.54 [0.49, 0.59]
H1a-b: Sharing behavior	self-relevance	—	0.04 [-0.68, 0.76]	—	—
	social relevance	—	1.01 [0.06, 1.96]	—	—
H2a: Self-relevance	other - control	0.46 [0.37, 0.54]	0.06 [-0.01, 0.13]	-0.01 [-0.06, 0.05]	0.12 [0.02, 0.21]
	self - control	0.38 [0.29, 0.47]	0.25 [0.18, 0.32]	0.02 [-0.03, 0.08]	0.42 [0.33, 0.51]
H2b: Social relevance	other - control	0.48 [0.39, 0.57]	0.19 [0.12, 0.25]	0.04 [-0.02, 0.09]	0.43 [0.34, 0.52]
	self - control	0.32 [0.24, 0.41]	0.14 [0.07, 0.20]	0.04 [-0.01, 0.10]	0.30 [0.21, 0.39]
H3: Broadcast sharing intention	other - control	0.47 [0.37, 0.57]	0.03 [-0.02, 0.08]	—	0.21 [0.14, 0.28]
	self - control	0.41 [0.31, 0.51]	0.04 [-0.01, 0.09]	—	0.17 [0.11, 0.24]
H3: Narrowcast sharing intention	other - control	0.44 [0.34, 0.54]	0.12 [0.06, 0.17]	-0.04 [-0.10, 0.02]	0.41 [0.32, 0.50]
	self - control	0.33 [0.23, 0.42]	0.09 [0.04, 0.15]	-0.05 [-0.11, 0.01]	0.26 [0.18, 0.35]
H3: Sharing behavior	other - control	—	0.71 [-0.54, 1.97]	—	—
	self - control	—	1.45 [0.25, 2.65]	—	—

Note. Parameter estimates for models with sharing behavior as the dependent variable are log odds. All statistics from each model is reported in Supplementary Material. Results from Study 4 are from the comment group only.

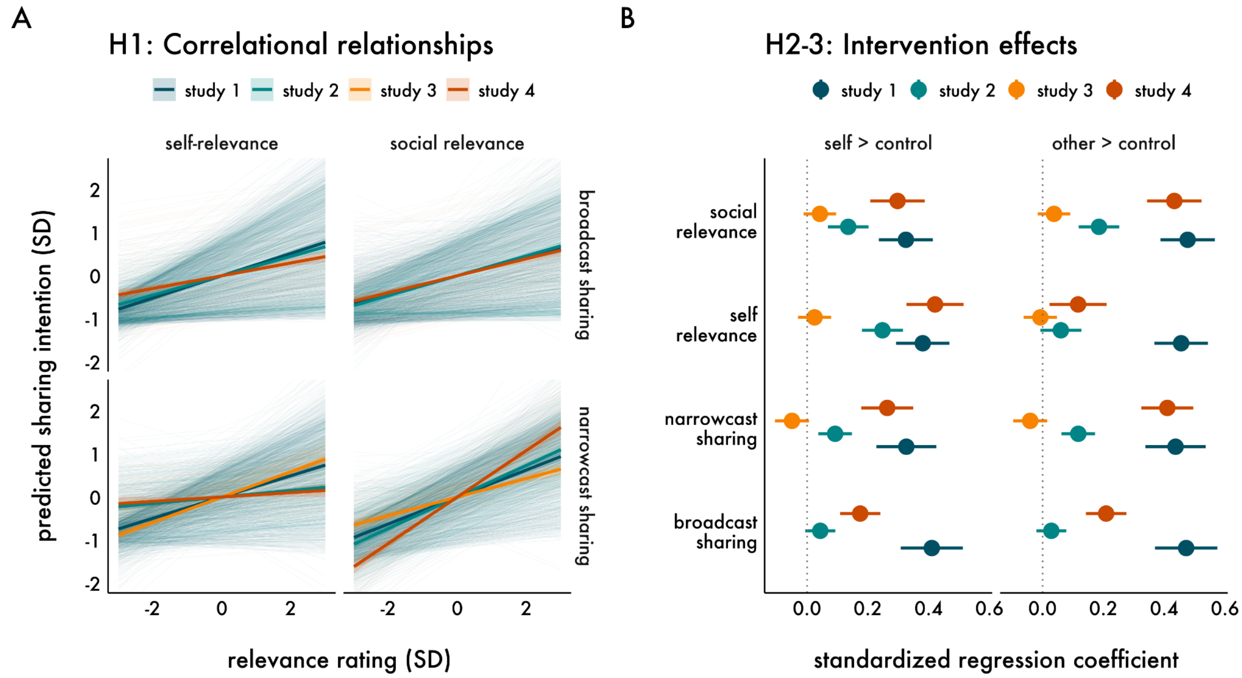

Figure 2. Results from the models testing hypotheses H1-3. (A) Correlational relationships between self and social relevance (x-axis) and intentions to share news articles (y-axis) broadly on social media ("broadcast sharing"; top panel) and directly with people e.g., via email or direct message ("narrowcast sharing"; bottom panel). Across all four studies, there are unique, positive correlational relationships among these variables. Model predicted values are overlaid on individual predicted slopes. Error bands are 95% confidence intervals. (B) Intervention effects (x-axis) of the content-framing interventions on self-relevance, social relevance, broad- and narrowcast sharing intentions (y-axis) for the self-focused intervention (left panel) and the other-focused intervention (right panel) versus the control condition or group. The largest effects tended to be in the online experiments using between-person (Study 1) and within-person (Study 4) designs, whereas the online field study interventions (Study 2) showed more modest effects and the MRI-adapted interventions without the writing component (Study 3) were not effective. The dotted line at zero represents no difference between the intervention and control condition; estimates greater than zero indicate positive intervention effects. Error bars are 95% confidence intervals. Results from Study 4 are from the comment group only.

H2: Content-framing interventions increase perceived news relevance when people engage

Next, we sought to confirm that the content-framing interventions causally influence their intended targets. As expected, in Studies 1, 2, and 4 we found that relative to a control condition, the self-focused framing intervention increased the perceived self-relevance of news articles and the other-focused framing intervention increased perceived social relevance (Table 2). However, when participants completed a version of the content-framing interventions adapted for the MRI scanner—in which they were instructed to reflect on relevance but did not write comments—neither intervention increased perceptions of relevance compared to the control condition. Given these results, Study 4 examined how different factors affecting engagement (reflecting versus writing comments, and the amount of reflection time allowed—12s versus unlimited time) impacted intervention effectiveness. Consistent with the findings from the prior studies, participants who were randomly assigned to complete the content-framing interventions by writing comments (as in Studies 1-2) rated health and climate news articles are more self and socially relevant and reported higher intentions to share them compared to participants who reflected by did not write comments (as in Study 3; results are reported in Table S16). Consistent with the idea that deeper engagement (e.g., through writing) is necessary for the content-framing interventions to work, we found that writing longer comments was associated with higher perception of self and social relevance, as well as news sharing intentions in Studies 1, 2, and 4 (Table S4).

Joint estimates for the relationship between the content-framing interventions and self-relevance across studies in which participants wrote comments (Studies 1, 2, and 4) are as follows: $\beta = 0.33$, 95% CI [0.29, 0.38], $t(11755.30) = 14.73$, $p < .001$ for the self-focused intervention and $\beta = 0.17$, 95% CI [0.12, 0.21], $t(11784.77) = 7.50$, $p < .001$ for the other-focused intervention. Joint estimates across these studies for relationship between the content-framing interventions and social relevance are as follows: $\beta = 0.22$, 95% CI [0.18, 0.27], $t(11993.83) = 10.00$, $p < .001$ for the self-focused intervention and $\beta = 0.31$, 95% CI [0.27, 0.35], $t(12017.22) = 13.94$, $p < .001$ for the other-focused intervention.

H3: Content-framing interventions increase news sharing when people engage

We next extended the correlational analyses testing hypothesis H1 to examine the causal relationships between relevance and sharing (Table 2). Participants who were randomized to either the self- or other-focused intervention groups in Study 1 reported higher intentions to share news articles about climate change compared to a between-person control group. These effects are mirrored in Study 2, which used a within-person design and exposed participants to full articles in a more naturalistic environment. When participants were prompted to describe why the articles were relevant to themselves (self-focused condition) or people they know (other-focused condition), they reported higher intentions to share them compared to when they described what the articles were about. Furthermore, identifying why the articles were relevant to themselves increased the probability of actually sharing the articles on social media or via email. In Study 3, we found additional evidence that the MRI-adapted version of the content-framing interventions (without a writing component) was not effective; neither the self- nor other-focused interventions increased intentions to share the news articles. Joint estimates for the relationship between the self-focused intervention and sharing across studies in which participants wrote comments (Studies 1, 2, and 4) are as follows: $\beta = 0.13$, 95% CI [0.09, 0.16], $t(12496.20) = 6.98$, $p < .001$ for broadcast sharing and $\beta = 0.18$, 95% CI [0.14, 0.22], $t(12661.91) = 8.77$, $p < .001$ for narrowcast sharing. Joint estimates for the relationship between the other-focused intervention and sharing in these studies are as follows: $\beta = 0.13$, 95% CI [0.10, 0.17], $t(12489.43) = 7.23$, $p < .001$ for broadcast sharing and $\beta = 0.24$, 95% CI [0.20, 0.28], $t(12661.68) = 12.05$, $p < .001$ for narrowcast sharing.

We also tested the degree to which intervention-related effects on sharing were mediated by self and social relevance in supplementary analyses. In studies with the strongest intervention-related effects (Studies 1 and 4), we generally replicated our prior research (Cosme et al., 2022) showing dual pathways through self and social relevance (Tables S10-11). In studies with weaker effects (Studies 2-3), we did not generally observe evidence of mediation.

H4: Activity in self and social brain regions is positively correlated with perceived news relevance

Study 3 examined the neuropsychological mechanisms underlying decisions to share high-quality news using functional neuroimaging. Whole-brain analyses reported in Supplementary Material indicated that both the self- and other-focused interventions increased activation in precuneus and posterior cingulate cortex, which are key nodes in the self and social processing systems (Northoff et al., 2006; Pfeifer & Peake, 2012; Saxe, 2006). In preregistered ROI analyses, we found that stronger activity in the self-referential ROI was positively correlated with self-reported perceptions of the self-relevance of the news articles (Table 3). In parallel, stronger activity in the social cognition ROI was positively correlated with self-reported perceptions of social relevance. This suggests that both self-reported perceptions and functional brain activation are sensitive to self-related and social motivations to share.

Table 3
Results from Study 3 models testing hypotheses H4-6

Dependent variable	Term	*β* [95% CI]	*df*	*t*	*p*
H4a: Self-relevance	intercept	-0.01 [-0.08, 0.07]	84.10	-0.20	.841
	self-referential ROI	0.05 [0.02, 0.07]	82.76	3.68	< .001
H4b: Social relevance	intercept	-0.02 [-0.10, 0.07]	84.49	-0.41	.685
	social cognitive ROI	0.05 [0.02, 0.08]	83.18	3.80	< .001
H5a: Narrowcast sharing intention	intercept	-0.01 [-0.08, 0.06]	84.43	-0.27	.791
	self-referential ROI	0.08 [0.05, 0.11]	81.64	6.11	< .001
H5b: Narrowcast sharing intention	intercept	-0.02 [-0.10, 0.05]	85.39	-0.66	.511
	social cognitive ROI	0.07 [0.05, 0.10]	81.87	5.48	< .001
H6a: Self-referential ROI	intercept (control)	0.08 [-0.03, 0.20]	84.07	1.46	.147
	other - control	0.09 [0.01, 0.16]	83.53	2.19	.032
	self - control	0.09 [0.00, 0.17]	83.67	2.06	.043
H6b: Social cognitive ROI	intercept (control)	0.33 [0.22, 0.44]	84.10	5.93	< .001
	other - control	0.06 [-0.02, 0.14]	83.34	1.58	.117
	self - control	0.07 [-0.01, 0.16]	83.73	1.72	.089

Note. Degrees of freedom were calculated using the Satterthwaite approximation

H5: Activity in self and social brain regions is positively correlated with news sharing intentions

Although the MRI-adapted reflection-only content-framing interventions were not as effective as the writing interventions in Studies 1 and 2, we observed correlational evidence that is consistent with the hypothesis that self and social motives influence sharing. Replicating prior findings (Baek et al., 2017; Scholz, Baek, et al., 2020), we found that stronger activity in brain regions implicated in self-referential processing and social cognition during news exposure was associated with higher intentions to share the news articles (Table 3). Furthermore, compared to models that included either self-reported relevance (H1) or ROI activity (H5) alone, combining self-reported and brain indices improved model fit in both the self and social models (Supplementary Table S14). In these combined models, all variables remained statistically significant predictors of news sharing, demonstrating that they are complementary indices of self and social motives that account for unique variance (Supplementary Table S15).

H6: Content-framing interventions increase activity in self-referential brain regions

Examining the causal effects of the content-framing interventions on brain activity, we found that both the self- and other-focused interventions increased activity in brain regions associated with self-referential processing (Table 3). We found directional increases for both content-framing interventions in brain regions associated with social cognition, but these increases were not statistically significant.

Exploratory analyses

In order for the content-framing interventions to be useful tools to increase sharing of high-quality news, they should generalize in various ways. The following exploratory analyses assess the degree to which the hypothesized relationships tested in H1-6 generalize across news topic (health or climate news) and cultural context (USA or the Netherlands). We also examine whether these interventions have downstream impacts on climate-related beliefs, attitudes, and behaviors.

News topic: Causal effects tend to be consistent across climate and heath news

We explored the degree to which the correlational and causal relationships testing H1-6 were moderated by article topic (climate or health) in Studies 2, 3, and 4 (comment group only). Study 1 was not included in this analysis because all news stimuli pertained to climate. Overall, we found that although there are mean-level differences between climate and health news articles in perceptions of relevance, brain activity, and sharing intentions, the content-framing interventions tended to be similarly effective across article topics. Results are reported in Supplementary Material (Tables S5-6).

Culture: Relationships tend to be consistent across American and Dutch samples

Study 3 allowed us to examine the generalizability of the correlational and causal relationships across two cultural contexts—USA and the Netherlands—by adding culture as a moderator to the models testing hypotheses H1-6. Overall, the American cohort exhibited greater neural activity in the self-referential and social cognitive ROIs, but there were no other differences between the cohorts (Figure 3). This evidence of proximal generalizability across cultures suggests that individuals from disparate cultures may consider self and social motives for sharing in similar ways. Results are reported in Supplementary Material (Table S7).

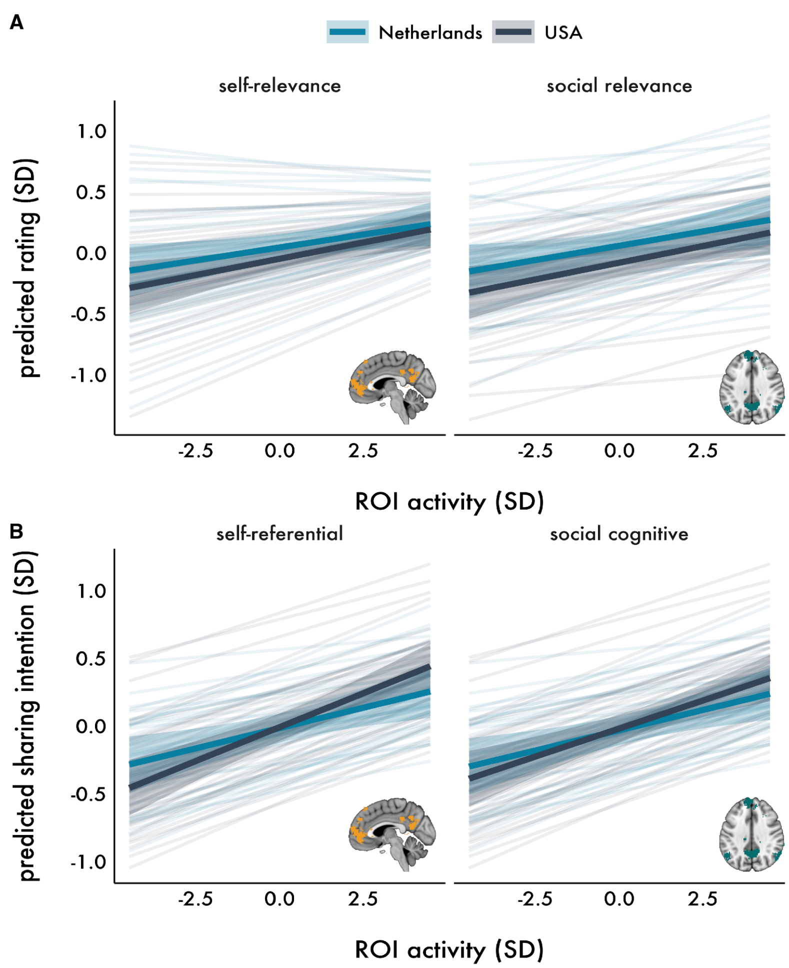

Figure 3. Results from the cultural comparison analysis. Both the American and Dutch cohorts showed positive relationships between activity in self-referential and social cognitive ROIs and predicted (A) self and social relevance ratings and (B) sharing intentions, and the magnitude of these associations were similar across cultures. Model predicted values are overlaid on individual predicted slopes. Error bands are 95% confidence intervals.

Climate action: Content-framing interventions have downstream effects on intentions to share petitions and perceived environmental impact of climate actions

Study 1 used a between-subjects design and focused on climate-related news, which afforded the ability to assess the impact of the content-framing interventions on downstream outcomes, such as intentions to share other information or engage in climate action. We found that both the self- and other-focused interventions' effects were not limited to news sharing. They also affected subsequent willingness to share petitions calling for climate action. Importantly, this finding demonstrates that reflecting on the self- and social-relevance of news articles can exert a lingering effect that generalizes to increase intentions to share other future content. Beyond sharing, we found that both interventions increased self-perceptions of climate knowledge relative to the control group. Furthermore, the other-focused intervention increased perceived self-efficacy of climate action, as well as the perceived environmental impact across all climate actions assessed. That is, participants who considered why climate news was relevant to people they know subsequently reported higher perceived impact of individual actions such as: driving and flying less, eating less meat and more vegetarian and vegan meals, paying for renewable energy, and recycling; and pro-environmental collective actions such as: signing petitions, volunteering, contacting political representatives, donating money, and talking with close others about climate change. Together, these exploratory results suggest that the content-framing interventions not only change how news is perceived, but have the potential to shift more distal beliefs, attitudes, and behavior. Results are reported in Supplementary Material (Table S8-9).

Discussion

Neural and behavioral research suggests that self-related and social motives drive information sharing. Drawing on these insights, we tested theory-based content-framing interventions to promote the sharing of high-quality news. Using a combination of experimental, field study, and cross-cultural fMRI methods, we observed robust and replicable evidence that targeting the self and social relevance of news increases willingness to share it. Across four studies, we replicated prior research showing positive associations among self-reported self and social relevance, activity in self-referential and social cognitive brain regions, and sharing intentions. When participants engaged with the intervention by writing prompted comments about the self and social relevance of news articles, the content-framing interventions increased perceptions of news as self and socially relevant, and increased sharing intentions and behavior. These relationships tended to generalize across topics (news articles about climate change and general health topics), across cultures (American and Dutch samples), and settings (laboratory, online, and naturalistic contexts that allowed actual sharing). Furthermore, the content-framing interventions also had downstream effects on intentions to share new information (not targeted in the intervention itself), attitudes, beliefs, and behavioral intentions. Theoretically, these findings add important neural and behavioral evidence that self-related and social motives prompt people to share information. Practically, they demonstrate that these motives can be activated through content-framing interventions to increase the spread of high-quality news. Together, this set of studies constitutes a major step forward in providing diverse practitioners—journalists, content creators, social activists, and public health officials—with evidence-based tools to influence sharing behavior.

Neuropsychological mechanisms of sharing

In line with theoretical predictions (Berger, 2014; Scholz, Jovanova, et al., 2020), when people perceived content as more self and socially relevant, or the content elicited stronger activity in brain regions associated with self-referential processing and social cognition, people reported stronger sharing intentions. The self-reported and neural measures also explained unique variance in sharing intentions, indicating that they are complementary measures that can be considered in tandem. Together with previous research examining more specific self and social goals (Scholz et al., 2023), self-reported self and social relevance (Cosme et al., 2022), and activity in these brain systems (Baek et al., 2017; Chan et al., 2023; Motoki et al., 2020; Scholz, Baek, et al., 2020; Scholz et al., 2017), these findings provide compelling evidence that self-related and social motives encourage sharing.

These findings advance the value-based framework of sharing, which highlights self-related and social motives as two important sources of value when deciding whether or not to share (Scholz, Jovanova, et al., 2020; Scholz & Falk, 2020). Whereas previous studies testing this framework have been primarily correlational in nature (Baek et al., 2017; Chan et al., 2023; Motoki et al., 2020; Scholz et al., 2017; Scholz, Jovanova, et al., 2020), this study adds critical causal evidence for the idea that self-related and social motives—here engaged through active reflection on the self and social relevance of information—encourage sharing and are supported by brain regions implicated in self-referential and social cognitive processes. Parallel mediation analyses showing indirect paths between the content-framing interventions and sharing through both self and social relevance provide convergent evidence for this causal model. These findings increase confidence that targeting these mechanisms can reliably influence high-quality news sharing in new situations and contexts.

Cross-cultural study of news sharing

We explored potential cultural differences in news processing and intervention effectiveness with American and Dutch samples. We did not observe evidence of moderation and the direction of relationships tended to be the same in each sample, suggesting proximal generalizability. This is further supported by a separate analysis of data from these participants showing that neural signals in both samples predicted population-level news sharing metrics (Chan et al., 2023). Given that the USA and the Netherlands are both Western, democratic, wealthy, industrialized countries that have similar but distinct cultural value structures (Minkov & Kaasa, 2022), it is important to extend these initial findings to a broader array of cultural contexts. Indeed, the strength of the relationships between self and social relevance and sharing may differ depending on how interdependent or independent a culture tends to be (Motoki et al., 2020). Although cross-cultural fMRI studies are resource intensive, our work suggests that explicit relevance ratings provide related indicators of self-related and social motives that can be used to study these relationships across cultures.

Translational implications

Translational interventions targeting self and social motives have the potential to increase the sharing of high-quality information, which in turn can shift social norms (Jeong & Bae, 2018; Tankard & Paluck, 2016) and catalyze broader attitudinal and behavioral change (Barberá et al., 2015). We found that prompting would-be sharers to identify their own reasons why news was relevant to themselves or others can increase their motivation to share, including in more ecologically valid contexts. This approach to promoting sharing is less labor-intensive and less context-dependent than content tailoring by content-creators (e.g. infusing sensationalism into content to make it more “shareable”). Consistent with the idea that self and social motives are fundamental (Deci & Ryan, 2000) and shape decision making (Falk & Scholz, 2018; Falk et al., in press), we also observed promising initial evidence that increasing the perceived self and social relevance of information has broader impacts on individuals. We found that the content-framing interventions affected not only news sharing, but also more distal beliefs, attitudes, and behavior related to the content.

For an intervention to be widely useful, it should also generalize in various ways. We found that the content-framing interventions were effective using both within- and between-person designs. They were effective across health and climate change articles and also across the American and Dutch samples. In a more ecologically valid paradigm, the direction of all associations replicated, although the magnitudes were somewhat weaker. Even still, small effects for individuals can have substantial impact at population scales. As information spreads throughout broad social networks, a single act of sharing could have cumulative impact by reaching many other individuals. This work is an promising initial step towards real-world translation, but iterative refinement of the intervention is necessary to increase its impact in more naturalistic contexts.

Limitations and future directions

Despite notable strengths—preregistration, replication, triangulation across neural, behavioral, and field study methods, the use of actual news stories, and inclusion of multiple cultural contexts—this research should be considered in light of limitations. Although the fMRI study focused on American and Dutch students to explore cross-cultural sharing motivation, the generalizability of results beyond these populations remains unclear. The behavioral studies extended the scope to broader adult samples in the USA, but these samples were somewhat less racially and ethnically diverse than the country as a whole. Study 2 provided preliminary evidence that the content-framing interventions increase actual sharing behavior, but given the low base rates of sharing, larger samples in future work are needed to accurately assess the magnitude of intervention-related changes in news sharing.

Conclusion

Our findings provide robust and replicable evidence that self-related and social concerns motivate sharing and highlight the potential of content-framing interventions to encourage people to share high-quality news. By increasing the quality of information circulating within social networks, individuals and society will be better equipped to make well-informed decisions and cooperate effectively toward shared goals.

Materials and methods

Detailed methods and power analyses for each study are reported in Supplementary Material.

Open practices statement

Study 1 (https://osf.io/7by85) and Study 3 (https://osf.io/2d35g) were preregistered prior to data collection. We deviated from our Study 3 preregistration in the following way: to retain mean differences in region of interest (ROI) activity between participants (and therefore enable intercepts to vary randomly across participants), ROI signals were standardized but not mean-centered within-person. The data and analysis code needed to reproduce the analyses in all studies are available online (https://github.com/cnlab/sharing-motivation). The stimuli used in this study are available online (https://osf.io/ak6wf).

Study 1

Participants

Participants (N = 1,687) were recruited using the online platform Prolific. Participants were aged 18-88 (M = 51.6, SD = 20) and reported the following gender identities: 51.9%

women, 45.6% men, 1.4% non-binary, 0.8% preferred to self-describe, and 0.2% did not report. Participants reported the following racial and ethnic identities: 69.7% White, 14.0% Black or African American, 9.7% Hispanic or Latina/o/x, 5.0% reported more than one race / ethnicity, 4.3% East Asian, 2.3% South Asian, 2.3% Southeast Asian, 0.4% American Indian or Alaskan Native, 0.1% Native Hawaiian or Other Pacific Islander, 1.3% identified with a race /ethnicity not list, and 0.7% preferred not to say. This study was approved by the University of Pennsylvania Institutional Review Board and all participants gave informed consent. In accordance with the standard operating procedures for this project (described in detail here: https://osf.io/6jufq), participants were excluded if they denied the existence or anthropogenic causes of climate change (n = 15), failed two attention checks (n = 4), were an outlier in responding invariantly across survey measures (n = 30), gave poor quality written responses (n = 15), self-reported data quality issues (n = 8, i.e., using ChatGPT or other AI tools for written responses, answering dishonestly or not taking the study seriously), or more than one of these reasons (n = 2). This yielded a final sample of N = 1,613. We also removed individual responses in which participants did not provide good faith responses, which we defined as writing five or fewer words or being flagged in quality assessment ($n_{responses}$ = 153, 1.90% of total responses).

Procedure

Study 1 uses a subset of data from a larger study comparing various psychological interventions to promote climate action (https://osf.io/x9c6j). This project contains other interventions and measures not discussed here. The content-framing interventions were adapted from Cosme et al., (2022) to use a between-person design. Participants were randomly assigned to one of the content-framing interventions—self-focused (N = 392) or other-focused (N = 387)—or a no-intervention control group (N = 834). All participants were exposed to five news headlines and ledes about climate change from the New York Times and rated them on the following dimensions: self-relevance (“This message is relevant to me”), social relevance (“This message is relevant to people I know”), broadcast sharing intention, (“I would share this article by posting on social media (on Facebook, Twitter, etc.)”), and narrowcast sharing intention (“I would share this article directly with someone I know (via email, direct message, etc.)”). Ratings were made on a scale from 0 (*strongly disagree*) to 100 (*strongly agree*). Participants in the self- and other-focused interventions also wrote brief comments for each article as if they were posting on social media describing why each article was relevant to themselves (self-focused; “Describe why this message matters to you personally”) or people they know (other-focused; “Describe why this message matters to people you know”). Each participant viewed five articles randomly selected from a pool of 26 articles.

After completing the content-framing interventions (or no intervention in the control group), participants completed climate action outcome measures and reported demographics. The climate action outcomes reported in this manuscript include petition sharing, perceived environmental impact of climate actions, perceived climate knowledge, and climate self-efficacy. These measures are described in more detail in Supplementary Material. Additional measures included in this project are described in the standard operating procedure (https://osf.io/6jufq).

Study 2

Participants

Participants were recruited using Prolific (N = 522). Participants were aged 18-78 (M = 38.07, SD = 12.28) and reported the following gender identities: 58.6% men, 40.9% women, and 0.003% did not report (no other gender options were provided on Prolific in this field study). Participants reported the following racial and ethnic identities: 70.1% White, 7.6% Asian, 10.7% Black or African American, 2.4% as another race or ethnicity, 7.6% Biracial, and 1.3% did not report their race. This study was approved by the WCG Institutional Review Board and all participants gave informed consent. Participants were excluded if there were technical issues during their participation, they failed the attention check or did not complete the full study (n = 52) or if they did not complete all three conditions at least once in the time allowed (n = 46). Participants were excluded if they completed an implausibly high number of trials within the 60 minute period, defined as being more than 3 *SD* from the median (n = 11; *Med* = 7, *SD* = 7.13) resulting in N = 413 participants for analysis. We removed individual responses in which participants did not provide good faith responses, which we defined as writing five or fewer words ($n_{\text{responses}}$ = 200, 5.2% of total responses).

Procedure

This study used a self-paced, within-person version of the same content-framing interventions from Study 1 on a platform designed to resemble a more natural online viewing experience (described in detail in Supplementary Material). Each participant completed both the self- and other-focused intervention conditions as well as a control condition in which participants wrote about what the articles were about. Participants viewed news articles about climate change and general health topics from the New York Times, and were presented with the entire text of the articles rather than headlines and ledes. Articles were randomly presented from a pool of 96 articles; the news article selection process is described in Supplementary Material. After reading the articles and writing comments according to the intervention condition, they made the same ratings as in Study 1. Participants also had the opportunity to share articles on Facebook, Reddit, LinkedIn, Email, or Twitter platforms by clicking the appropriate share button.

Study 3

Participants

Participants were recruited from two testing sites, universities in the Netherlands (n = 40) and Northeastern USA (n = 45). Participants were aged 18-31 (*M* = 21.4, *SD* = 2.5) and reported the following gender identities: 48.2% men, 48.2% women, 1.2% non-binary, 1.2% gender fluid, and 1.2% did not report. Participants reported the following racial and ethnic identities: 48.2% White, 16.5% East Asian, 11.8% Hispanic or Latina/Latino/Latinx, 8.2% Black or African American, 8.2% as another race or ethnicity, 7.1% Biracial, 5.9% South Asian, 2.4% Southeast Asian, and 1.2% preferred not to say, and 2.4% did not report their race or ethnicity. Participants were included if they were fluent in English, right-handed, and a university student or recent graduate. Participants were ineligible if they had any irremovable nonferrous metallic objects (i.e., implanted medical devices) or were currently pregnant or breastfeeding. Participants were also ineligible if they reported a history of substance abuse, major mental health diagnosis, or psychotropic medication use. This study was approved by the Institutional Review Boards at each study site and all participants gave informed consent.

Procedure

Participants were recruited as part of a larger project on news sharing (Chan et al., 2023) that included additional tasks and measures not considered in this manuscript (see project information online: https://osf.io/caxfq). After being enrolled in the study but prior to completing the MRI session, participants completed an online survey assessing various individual differences measures (https://osf.io/5hps4). At the MRI session, participants were trained and then completed an incentive-compatible version of the content-framing intervention task inside the MRI machine. This study used a within-person design similar to Study 2—each participant engaged in the self- and other-focused interventions and the control condition during the task. Participants viewed a random subset of 72 articles from the 96-article stimulus set used in Study 2 and reflected on the articles according to the intervention condition for 12s. Due to the constraints of the MRI machine, participants only reflected but did not write comments as in Studies 1-2. After reflecting, participants rated their intention to share the article with a person they identified prior to the task. After the MRI scan, they completed a post-scan rating task (described below). After the in-person session, participants were asked to share a randomly selected article they rated as being willing to share. Detailed methods about the task, neuroimaging acquisition, preprocess, analysis, ROI definition, and sensitivity analyses using alternatively defined ROIs are provided in Supplementary Material.

Study 4

Participants

This online study was conducted through Prolific. Participants were included if they were adults 18 or older, residing in the United States, fluent in English, and passed an initial attention test (N = 505). Participants were excluded if they failed the attention check (n = 0) or did not complete any items beyond a practice block (n = 57). Because more participants in the comment group (n = 3) than the reflection only groups (n = 1) did not complete the survey, we included all available data for these participants to reduce potential bias. We removed individual responses in which participants did not provide good faith responses, which we defined as writing five or fewer words ($n_{\text{responses}}$ = 51, 3.4% of total responses). This yielded a final sample of N = 448. Participants were aged 18-92 (M = 47.5, SD = 18.1). Participants reported the following gender identities: 48.2% men, 47.5% women, 2.2% non-binary, 0.7% preferred to self-describe their gender, 0.4% preferred not to say, and 0.9% did not report their gender. Participants reported the following racial and ethnic identities: 83.3% White, 7.8% Hispanic or Latina/Latino/Latinx, 5.6% Asian, 4.9% Black or African American, 3.6% More than one race, 1.6% preferred not to say, 0.2%, American Indian or Alaskan Native, and 0.9% did not report their race / ethnicity. This study was approved by the University of Pennsylvania Institutional Review Board and all participants gave informed consent.

Procedure

This study used a mixed design. Participants were randomly assigned to either the timed reflection (n = 159), untimed reflection (n = 169), or the comment (n = 131) group. As in Studies 2-3, participants in all groups viewed articles (n = 4) in the self-focused, other-focused, and control conditions, and viewed a subset of 12 articles from the set of 96. After reading and reflecting on the articles according to the intervention condition (self-focused, other-focused, or control), participants rated the articles on the same dimensions as in Studies 1-3. In the *reflection* groups (timed and untimed), participants read and reflected on the articles before rating the messages as they did in the MRI-adapted task version used in Study 2. In the timed group, participants had 12s to read and reflect, whereas in the untimed group, they had unlimited time. Mirroring the design in Study 2, participants in the *comment group* also wrote brief comments as if they were posting on social media in accordance with the content-framing intervention condition.

Statistical analyses

Hypotheses were tested with multilevel modeling using lme4 (Version 1.1-26; Bates et al., 2015) and lmerTest (Version 3.1-3; Kuznetsova et al., 2017) packages for significance testing in R (Version 3.6.3; R Core Team, 2022). Models with sharing behavior as the outcome use multilevel logistic regression with the glmer function from *lme4* (Version 1.1-26; Bates et al., 2015). Continuous variables were z-scored to facilitate interpretation of standardized effects. We strove for a maximal random effects structure to improve generalizability (Barr et al., 2013). In all models, intercepts and slopes were allowed to vary randomly across participants and articles unless the model did not converge or converged a singular fit, in which case random intercepts only were specified. When estimating relationships jointly across studies, intercepts were also allowed to vary randomly where possible. Degrees of freedom (df) were calculated using the Satterthwaite approximation. All p-values reported are from two-tailed tests.

Hypotheses H1–6 analyses

H1 was tested by regressing broadcast and narrowcast sharing intentions, and sharing behavior on the fixed effects of (a) self and (b) social relevance. H2 was tested by regressing (a) self-relevance and (b) social relevance on the fixed effect of intervention condition. H3 was tested by regressing broadcast and narrowcast sharing intentions, and sharing behavior on the fixed effects of intervention condition. H4 was tested by regressing (a) self-relevance on the fixed effect of self-referential ROI activity and (b) social relevance on the fixed effect of social cognitive ROI activity. H5 was tested by regressing narrowcast sharing intentions on the fixed effect of (a) self-referential ROI activity and (b) social cognitive ROI activity. H6 was tested by regressing (a) self-referential and (b) social cognitive ROI activity on the intervention condition. We also tested potential mediation of intervention-related effects on sharing through self and social relevance using Bayesian multilevel parallel mediation. These analyses are reported in Supplementary Material.

Study 4 analyses

Condition effects by group. We tested whether the comment group would be more effective than the reflection groups by regressing (a) self-relevance, (b) social relevance, (c) broadcast and (d) narrowcast sharing intentions on intervention condition, group, and their interaction. These analyses are reported in Supplementary Material.

Word count. In the comment group, we tested whether deeper engagement with the manipulation would lead to greater effectiveness by regressing (a) self-relevance, (b) social relevance, (c) broadcast and (d) narrowcast sharing intentions on word count. We replicate these analyses in Studies 1-2 and report them in Supplementary Material.

Exploratory analyses

Moderation analyses. We explored how the hypothesized relationships in H1-6 might differ as a function of article topic (climate change or health) and cultural context (USA or the Netherlands) by including the variable as an interaction term in the H1-6 models.

Climate action. We explored the degree to which the content-framing interventions increased intentions to share petitions about climate action using multilevel modeling and regressing (a) broadcast and (b) narrowcast sharing intentions on the fixed effects of intervention group. We examined the degree to which the content-framing interventions increased the perceived environmental impact of 12 individual and collective actions using multilevel modeling. We regressed perceived impact on the fixed effects of intervention group. We used linear regression to test group differences in perceived knowledge about climate change and self-efficacy.

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Positionality statement

In acknowledgement that our identities can influence our approach to science (Roberts et al., 2020), the authors wish to provide the reader with information about our backgrounds. With respect to gender, when the manuscript was drafted, 9 authors self-identified as women, 4 as men, and 1 as non-binary. With respect to race and ethnicity, 9 authors self-identified as White, 2 as White and Latinx, 1 as Asian, and 1 as White and Asian. With respect to nationality, 10 authors self-identified as American, 1 as Dutch, 1 as German, and 1 as American and Canadian. With respect to age, all authors are younger than 50.

Citation diversity statement

Recent work in several fields of science has identified a bias in citation practices such that papers from women and other minority scholars are under-cited relative to the number of such papers in the field (Bertolero et al., 2020; Caplar et al., 2017; Chatterjee & Werner, 2021; Dion et al., 2018; Dworkin et al., 2020; Fulvio et al., 2021; Maliniak et al., 2013; Mitchell et al., 2013; Wang et al., 2020). Here we sought to proactively consider choosing references that reflect the diversity of the field in thought, form of contribution, gender, race, ethnicity, and other factors. First, we obtained the predicted gender of the first and last author of each reference (excluding software package citations) by using databases that store the probability of a first name being carried by a woman (Caplar et al., 2017; Dion et al., 2018; Dworkin et al., 2020; Maliniak et al., 2013; Mitchell et al., 2013; Zhou et al., 2020). By this measure, our citations contain 35% women and 65% men across all authors from non-software references; 42% women and 57% men considering only first and last authors from non-software references; and 100% men across software references. This method is limited in that a) names, pronouns, and social media profiles used to construct the databases may not, in every case, be indicative of gender identity and b) it cannot account for intersex, non-binary, or transgender people.

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Perceived self and social relevance of content motivates news sharing across cultures and topics

Supplementary Material

Study 1 methods

Power

We conducted power analyses to determine the sample size per intervention group. N = 400 per intervention group would give >87% power to detect between-group differences in message-level effects (e.g. with 5 repeated measures) sized d = 0.15 or larger and 80% power to detect between-group differences in person-level effects (i.e., with a single measure per person) sized d = 0.2 or larger. Because intervention groups in the broader project would each be compared to a common control, we recruited a larger control group (N = 800) to reduce noise and increase the precision of the estimates in this group.

Climate action outcomes

Petitions. Participants viewed three petitions about climate change (screenshots of real petitions sourced from *change.org* accompanied by abbreviated text), randomly selected from a larger set of 10 petitions. For each petition presented, participants used a scale from 0 (*strongly disagree*) to 100 (*strongly agree*), to rate their intentions to share the petition broadly on social media or directly with someone they know.

Perceived environmental impact. Participants were asked about 12 actions that could have positive or negative effects on climate change. The list of actions included seven individual actions (eating beef or lamb, eating vegetarian meals, eating vegan meals, driving a fuel-powered vehicle, flying by airplane, recycling, and paying for renewable energy to power one's home) and five collective actions (donating, volunteering, signing petitions, contacting representatives, and talking to others about climate change). Actions were presented in a randomized order, with a single action presented per page. For each action, participants used 7-point scales to rate the perceived environmental impact if many people did the action more/less often (1 = *No impact*, 7 = *Very large impact*). Actions were framed in terms of engaging "more" or "less" depending on which direction would indicate pro-environmental behavior (e.g., driving *less*, donating *more*).

Perceived climate change knowledge. We measured climate knowledge using 2 items with a 5-point agreement scale (1 = *Strongly disagree*, 5 = *Strongly agree*). The items included: (1) Knowing about environmental problems is important to me. (2) I know a lot about climate change and the environment.

Climate self-efficacy. We measured self-efficacy (i.e., belief in our ability, as individuals and as a society, to take action to address climate change) with a subset of four items selected from the Climate Change Attitude Survey (Chirstensen & Knezek, 2015). Participants responded with a 5-point agreement scale (1 = *Strongly disagree*, 5 = *Strongly agree*). The items included: (1) The actions of individuals can make a positive difference in global climate change. (2) We cannot do anything to stop global climate change. (3) There are actions I can take to reduce the impact of climate change. (4) It is a waste of time to work to solve environmental problems.

Study 2 methods

Power

Sample size was determined by a power analysis indicating that a sample size of 500 (with at least two articles per condition) would achieve >80% power to detect an effect size of d = 0.10 or larger. The number of people who had at least two articles per condition (N = 379)—which was necessary for the multilevel power calculation—gave us >80% power to detect an effect size of d = 0.12 or larger. Given that we also included participants with only a single article condition (*N* = 34) in analyses, we likely have slightly higher power to detect this effect size.

Procedure

This study used a self-paced, within-person design on a platform designed to resemble a more natural online viewing experience. With consent, the plug-in recorded their navigation within the browser, including mouse clicks and scrolls. There was nothing overt or noticeable to the user in the browser, beyond the consent and experimental setup. The news articles were presented (full-text) on the left 60% of the screen. The right 40% of the screen displayed the condition prompt, relevance questions, and sharing intention questions. Participants were presented with the entire text of a randomly selected article. They were instructed to answer the study questions (right panel) after completion of each article. There was no time limit on each article but the overall study did not display a new article after 35 minutes. On average, participants read 8 articles (*SD* = 4.67, range = 1-27).

After reading and reflecting on the articles according to the framing condition (self-focused, other-focused, or control), participants rated how self ("This message is relevant to me") and socially relevant ("This message is relevant to people I know") they perceived the article to be. They also rated their broadcast intention to share the article on social media ("I would share this article by posting on social media (on Facebook, Twitter, etc)") and narrowcast intention to share it directly with someone ("I would share this article directly with someone I know (via email, direct message, etc)"). All ratings were made using the following scale, in increments of 10: 0 = *strongly disagree*, 100 = *strongly agree*. As in Study 1, participants wrote brief comments as if they were posting on social media in accordance with the framing condition. In the self-focused condition they wrote a comment describing *why the article is relevant to themselves*; in the other-focused condition they wrote a comment describing *why the article is relevant to people they know*; and in the control condition they wrote a comment describing *what the article was about.*

Stimuli. Stimuli consisted of 96 news articles (headlines and ledes) about general health (*n* = 48) and climate change (*n* = 48) published by the New York Times between 2016 and 2019. Articles were purposefully selected: we chose articles with word counts in a range (*min* = 21, *max* = 44, *M* = 31.91, *SD* = 5.55) that was deemed convenient for presentation online and in the MRI scanner. Articles about specific time-sensitive issues or events and articles with highly American-centric topics were excluded since scanning took place over the course of multiple months and in both American and European samples. Finally, we chose articles of varying real-world virality (Chan et al., 2023) across the topics of health (range of share counts of the news articles on Facebook public pages: 58 - 22,039) and climate change (range of share counts: 44 - 25,091).

Study 3 methods

Power

The sample size (*N* = 85) was determined by grant funding. We conducted a within-person experiment examining trial-level data (*N* observations = 6,014), which yielded >80% power to detect small differences between framing conditions (*d* = 0.08).

Sharing task

Design. Participants completed an incentive-compatible news sharing task adapted from Cosme et al. (2022) in which they were exposed to news article abstracts and reflected on them in different ways while undergoing functional neuroimaging. Before the task, participants identified five people they knew that were interested in general health topics and climate change with whom they would be invited to share one of the articles. They were instructed to consider these people when rating their intentions to share. After completing the in-person session, they were sent a randomly selected article for which they indicated a positive sharing intention and were asked to send it to one of the five identified people. The task used a within-person design with three conditions: self-focused, other-focused, and a control condition (Figure 2). In the self-focused condition, we manipulated self-relevance by asking participants to reflect on *why the article is relevant to themselves*. In the other-focused condition, we manipulated social relevance by asking participants to reflect on *why the article is relevant to people they know*. In the control condition, participants *reflected on the article content*. Each condition was signified by a text cue that had a different text color; color assignment was randomized across participants. Each participant was exposed to a random subset of 72 articles from the 96-article stimulus set because of time constraints. Articles were pseudo-randomized in each task run and condition such that they: 1) contained an equal number of climate and health news articles; 2) contained an equal number of news articles from each quartile of virality; and 3) were seen by approximately the same number of participants.

The task consisted of three runs each containing 24 trials (five participants in the Dutch sample completed an earlier version of the task that used two runs of 36 trials each). The task employed a quasi-block design to reduce burden associated with task switching, while allowing event-related modeling. Six blocks (two per condition, consisting of four trials per block) were presented in each task run. Each block began with a condition cue (3s), followed by a fixation cross (1s), and then participants completed four trials according to the condition. In each trial, participants viewed the news abstract and reflected on it based on the condition (12s) and then rated their intention to share the abstract with someone they know (3s) using the following scale: -2 = *strong no*, -1 = *no*, 1 = *yes*, 2 = *strong yes*, recoded to a continuous variable of 1-4 for analysis. Thus, this experiment focused on narrowcast sharing—i.e., sharing with a small well-defined audience—as opposed to broadcast sharing—i.e., sharing broadly with a loosely-defined, large audience, (e.g. on social media). A jittered fixation cross was shown between trials (M = 3.0s, min = 1.4s, max = 6.0s, drawn from a gamma distribution with alpha = 0.6, beta = 2). The task was programmed using PsychoPy (Version 3.2; Peirce, 2007). Participants made responses using a 4-button box while in the MRI scanner.

Post-scan ratings. Participants viewed each news headline and abstract again without the condition cues after the MRI scan to rate how self-relevant ("This article is relevant to me.") and socially relevant ("This article is relevant to people I know.") using the same rating scale as in the sharing task.

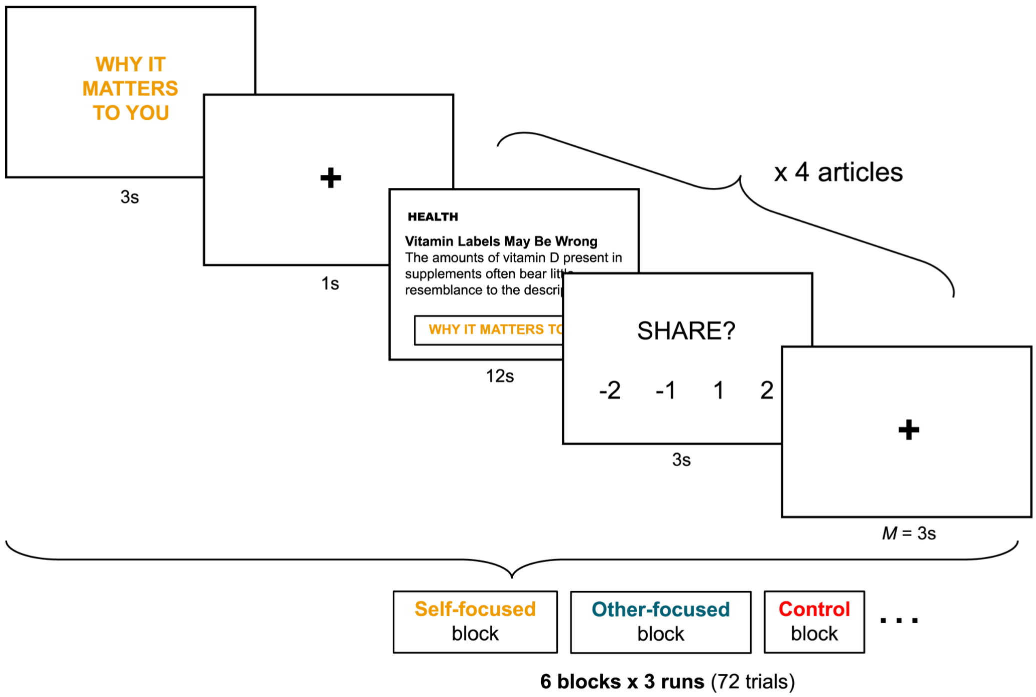

Figure S1. Sharing task design. Participants were exposed to news articles, reflected on them in different ways, and rated their intention to share the articles with pre-selected people. The task used a within-person design with three conditions. In the self-focused condition, we manipulated self-relevance by asking participants to reflect on why the article is relevant to themselves. In the other-focused condition, we manipulated social relevance by asking participants to reflect on why the article is relevant to people they know. In the control condition, participants reflected on the article content.

Neuroimaging acquisition

MRI scans were acquired at two scanning sites—one in the USA, and one in the Netherlands. At the American site, data were collected on a Siemens 3-Tesla scanner with a 64 channel head coil. We started by collecting a high-resolution 3D T1-weighted scan for anatomical reference (FOV = 192 × 256 × 224 mm; TR = 2.15s; TE = 0.00388s; FA = 8°; voxel size = 1.0 × 1.0 × 1.0 mm). While participants completed the behavioral tasks, functional scans were collected using a multiband echo-planar imaging (EPI) technique (multiband factor = 4; FOV = 240 × 240 × 118.8 mm; TR = 0.55s; TE = 30ms; FA = 55°; voxel size = 3.0 × 3.0 × 3.3 mm; slice gap = 0.3mm). At the Dutch site, data was collected on a Philips 3-Tesla scanner with a 32 channel head coil. A high-resolution T1-weighted scan for anatomical reference was first collected using Philip's SENSE parallel imaging technique (FOV = 242 × 242 × 220 mm; TR = 0.0082s; TE = 0.0037s; FA = 8°; voxel size: 0.9 × 0.9 × 1.0 mm). While participants completed the behavioral tasks, functional scans were collected using a multiband echo-planar imaging (EPI) technique (multiband factor = 4; FOV = 240 × 240 × 118.5 mm; TR = 0.55s; TE = 30ms; FA = 55°; voxel voxel size = 3.0 × 3.0 × 3.3 mm; slice gap = 0.3mm).

Neuroimaging preprocessing

Neuroimaging data were preprocessed using fMRIPrep 20.0.6 (Esteban et al., 2019).

Anatomical data preprocessing. The T1-weighted (T1w) image was corrected for intensity non-uniformity (INU) with N4BiasFieldCorrection (Tustison et al. 2010), distributed with ANTs 2.2.0 (Avants et al. 2008, RRID:SCR_004757), and used as T1w-reference throughout the workflow. The T1w-reference was then skull-stripped with a Nipype implementation of the antsBrainExtraction.sh workflow (from ANTs), using OASIS30ANTs as target template. Brain tissue segmentation of cerebrospinal fluid (CSF), white-matter (WM) and gray-matter (GM) was performed on the brain-extracted T1w using fast (FSL 5.0.9, RRID:SCR_002823, Zhang, Brady, & Smith 2001). Brain surfaces were reconstructed using recon-all (FreeSurfer 6.0.1, RRID:SCR_001847, Dale, Fischl, and Sereno 1999), and the brain mask estimated previously was refined with a custom variation of the method to reconcile ANTs-derived and FreeSurfer-derived segmentations of the cortical gray-matter of Mindboggle (RRID:SCR_002438, Klein et al. 2017). Volume-based spatial normalization to one standard space (MNI152NLin2009cAsym) was performed through nonlinear registration with antsRegistration (ANTs 2.2.0), using brain-extracted versions of both T1w reference and the T1w template. The following template was selected for spatial normalization: ICBM 152 Nonlinear Asymmetrical template version 2009c [Fonov et al. (2009), RRID:SCR_008796; TemplateFlow ID: MNI152NLin2009cAsym],

Functional data preprocessing. For each of the BOLD runs per participant (across all tasks and sessions), the following preprocessing was performed. First, a reference volume and its skull-stripped version were generated using a custom methodology of fMRIPrep. A deformation field to correct for susceptibility distortions was estimated based on fMRIPrep's fieldmap-less approach. The deformation field is that resulting from co-registering the BOLD reference to the same-subject T1w-reference with its intensity inverted (Wang et al. 2017; Huntenburg, 2014). Registration is performed with antsRegistration (ANTs 2.2.0), and the process regularized by constraining deformation to be nonzero only along the phase-encoding direction, and modulated with an average fieldmap template (Treiber et al. 2016). Based on the estimated susceptibility distortion, a corrected EPI (echo-planar imaging) reference was calculated for a more accurate co-registration with the anatomical reference. The BOLD reference was then co-registered to the T1w reference using bbregister (FreeSurfer) which implements boundary-based registration (Greve & Fischl, 2009). Co-registration was configured with six degrees of freedom. Head-motion parameters with respect to the BOLD reference (transformation matrices, and six corresponding rotation and translation parameters) are estimated before any spatiotemporal filtering using mcflirt (FSL 5.0.9, Jenkinson et al. 2002). The BOLD time-series (including slice-timing correction when applied) were resampled onto their original, native space by applying a single, composite transform to correct for head-motion and susceptibility distortions. These resampled BOLD time-series will be referred to as preprocessed BOLD in original space, or just preprocessed BOLD. The BOLD time-series were resampled into standard space, generating a preprocessed BOLD run in MNI152NLin2009cAsym space. First, a reference volume and its skull-stripped version were generated using a custom methodology of fMRIPrep. Several confounding time-series were calculated based on the preprocessed BOLD: framewise displacement (FD), DVARS and three region-wise global signals. FD and DVARS are calculated for each functional run, both using their implementations in Nipype (following the definitions by Power et al. 2014). The three global signals are extracted within the CSF, the WM, and the whole-brain masks. Additionally, a set of physiological regressors were extracted to allow for component-based noise correction (CompCor, Behzadi et al. 2007). Principal components are estimated after high-pass filtering the preprocessed BOLD time-series (using a discrete cosine filter with 128s cut-off) for the two CompCor variants: temporal (tCompCor) and anatomical (aCompCor). tCompCor components are then calculated from the top 5% variable voxels within a mask covering the subcortical regions. This subcortical mask is obtained by heavily eroding the brain mask, which ensures it does not include cortical GM regions. For aCompCor, components are calculated within the intersection of the aforementioned mask and the union of CSF and WM masks calculated in T1w space, after their projection to the native space of each functional run (using the inverse BOLD-to-T1w transformation). Components are also calculated separately within the WM and CSF masks. For each CompCor decomposition, the k components with the largest singular values are retained, such that the retained components' time series are sufficient to explain 50 percent of variance across the nuisance mask (CSF, WM, combined, or temporal). The remaining components are dropped from consideration. The head-motion estimates calculated in the correction step were also placed within the corresponding confounds file. The confound time series derived from head motion estimates and global signals were expanded with the inclusion of temporal derivatives and quadratic terms for each (Satterthwaite et al. 2013). Frames that exceeded a threshold of 0.5 mm FD or 1.5 standardized DVARS were annotated as motion outliers. All resamplings can be performed with a single interpolation step by composing all the pertinent transformations (i.e. head-motion transform matrices, susceptibility distortion correction when available, and co-registrations to anatomical and output spaces). Gridded (volumetric) resamplings were performed using antsApplyTransforms (ANTs), configured with Lanczos interpolation to minimize the smoothing effects of other kernels (Lanczos, 1964). Non-gridded (surface) resamplings were performed using mri_vol2surf (FreeSurfer).Preprocessed functional data were smoothed using a 6mm full-width at half maximum (FWHM) smoothing kernel.

Statistical modeling. First-level (i.e., participant-specific) statistical analyses were conducted in MNI space in SPM12 (Wellcome Department of Cognitive Neurology; http://www.fil.ion.ucl.ac.uk/spm) using nipype (Gorgolewski et al., 2011). For each participant, we fit a general linear model (GLM) in which trials were entered as separate regressors and the canonical hemodynamic response function was convolved on stimulus events. Trial duration was defined as the duration of the news abstract presentation. Block instructions and ratings were included as regressors of no interest. We also included the following regressors to account for motion: absolute displacement from the origin in Euclidean distance and the displacement derivative for both translation and rotation, dummy-coded motion artifact outliers (defined as framewise displacement > .75mm), and cerebrospinal fluid average signals. All data were high-pass filtered at 128 s, and temporal autocorrelation was modeled using FAST. The GLM yielded single-trial beta maps, representing the whole-brain neural responses to each news abstract. Because motion artifacts may persist in the beta-series, we calculated the mean global intensity for each beta map and excluded trials (n = 1.5%) that were more than 3 *SD* from the mean, calculated within-person and ROI.

ROI definition and signal extraction

Preregistered *a priori* brain regions of interest (Figure S2) were defined using automated meta-analytic maps (obtained via Neurosynth.org; Yarkoni et al., 2011) for the following terms: “self referential” and “mentalizing.” We used association maps, which indicate how much more likely activation is reported in a region given that a term is present (vs. absent) from a paper, and created a binarized mask by thresholding at p < .01 (FDR corrected). Voxel signals were averaged within each ROI for each single-trial beta image and then standardized within person. We complement these ROI analyses with whole-brain analyses.

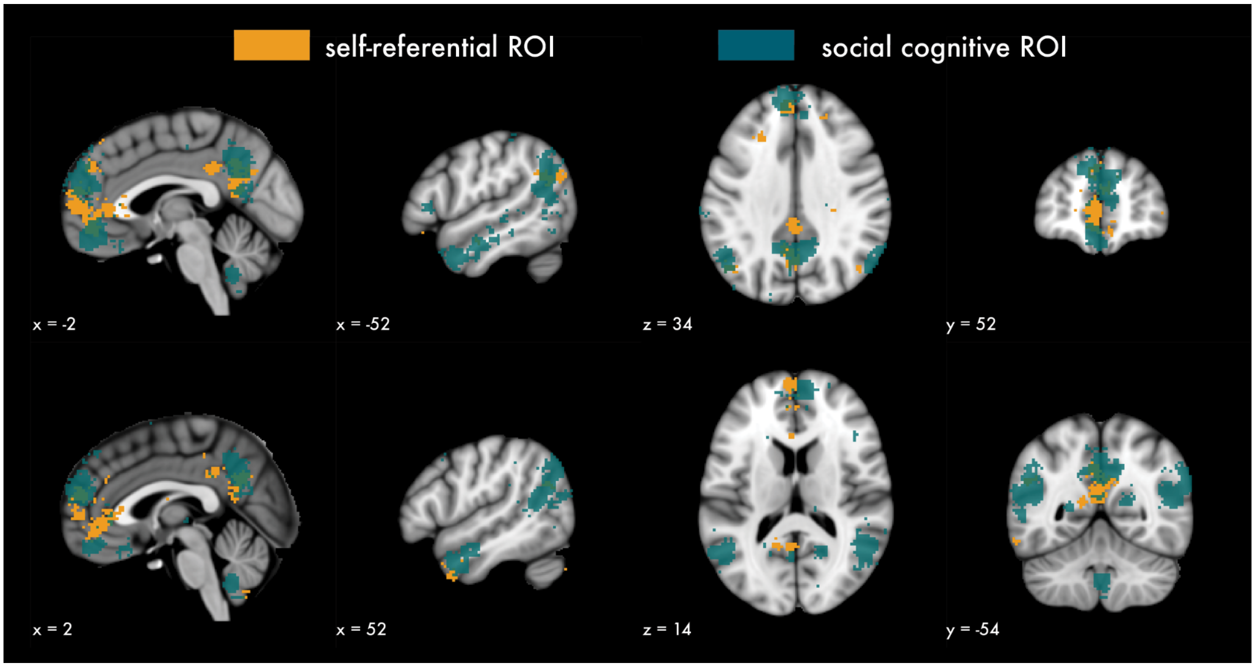

Figure S2. Preregistered *a priori*, meta-analytically defined regions of interest for self-referential processing and social cognition.

Study 4 methods

Power. Sample size was determined by a power analysis indicating that a sample size of 405 (n = 135 per condition) would achieve >80% power to detect a condition by group interaction effect size of d = 0.1 or larger.

Main manuscript analysis tables

H1 statistical models

Table S1 reports the full statistical models for the analyses testing H1 in the main manuscript (reported in Table 2).

Table S1
Results from the models testing H1

Study	Sharing type	Term	β [95% CI]	*df*	*t*	*p*
Study 1	broadcast sharing	self-relevance	0.26 [0.23, 0.29]	679.67	16.28	< .001
		social relevance	0.21 [0.18, 0.24]	753.19	12.75	< .001
	narrowcast sharing	self-relevance	0.25 [0.21, 0.28]	771.40	13.63	< .001
		social relevance	0.31 [0.28, 0.35]	829.49	17.38	< .001
Study 2	broadcast sharing	self-relevance	0.22 [0.19, 0.26]	224.22	11.66	< .001
		social relevance	0.23 [0.20, 0.26]	239.54	13.12	< .001
	narrowcast sharing	self-relevance	0.08 [0.04, 0.11]	2621.50	4.39	< .001
		social relevance	0.37 [0.33, 0.40]	2876.63	20.75	< .001
Study 3	narrowcast sharing	self-relevance	0.29 [0.26, 0.33]	90.93	15.35	< .001
		social relevance	0.22 [0.17, 0.26]	83.69	9.16	< .001
Study 4	broadcast sharing	self-relevance	0.15 [0.10, 0.19]	1273.66	6.71	< .001
		social relevance	0.20 [0.15, 0.24]	1346.21	8.43	< .001
	narrowcast sharing	self-relevance	0.05 [0.00, 0.10]	1329.89	1.99	.047
		social relevance	0.54 [0.49, 0.59]	1402.35	19.90	< .001

H2 statistical models

Table S1 reports the full statistical models for the analyses testing H2 in the main manuscript (reported in Table 2).

Table S2
Results from the models testing H2

Study	Variable	Term	β [95% CI]	*df*	*t*	*p*
Study 1	self-relevance	intercept (control)	-0.20 [-0.31, -0.10]	40.60	3.94	< .001
		other - control	0.46 [0.37, 0.54]	1614.83	10.14	< .001
		self - control	0.38 [0.29, 0.47]	1613.11	8.50	< .001
	social relevance	intercept (control)	-0.19 [-0.30, -0.09]	40.61	3.70	< .001
		other - control	0.48 [0.39, 0.57]	1613.52	10.47	< .001
		self - control	0.32 [0.24, 0.41]	1611.87	7.16	< .001
Study 2	self-relevance	intercept (control)	-0.06 [-0.16, 0.03]	376.42	1.39	.166
		other - control	0.06 [-0.01, 0.13]	2881.55	1.74	.081
		self - control	0.25 [0.18, 0.32]	2891.52	7.17	< .001
	social relevance	intercept (control)	-0.07 [-0.16, 0.02]	453.86	1.56	.120
		other - control	0.19 [0.12, 0.25]	2884.21	5.45	< .001
		self - control	0.14 [0.07, 0.20]	2894.18	3.96	< .001
Study 3	self-relevance	intercept (control)	-0.00 [-0.11, 0.10]	195.45	0.09	.928
		other - control	-0.01 [-0.06, 0.05]	5935.04	0.27	.789
		self - control	0.02 [-0.03, 0.08]	5934.05	0.88	.377
	social relevance	intercept (control)	-0.03 [-0.14, 0.08]	180.96	0.46	.647
		other - control	0.04 [-0.02, 0.09]	5934.94	1.37	.169
		self - control	0.04 [-0.01, 0.10]	5933.92	1.54	.124
Study 4	self-relevance	intercept (control)	-0.18 [-0.31, -0.04]	223.50	2.51	.013
		other - control	0.12 [0.02, 0.21]	1265.69	2.44	.015
		self - control	0.42 [0.33, 0.51]	1268.12	8.79	< .001
	social relevance	intercept (control)	-0.24 [-0.38, -0.10]	183.91	3.42	< .001
		other - control	0.43 [0.34, 0.52]	1286.02	9.46	< .001
		self - control	0.30 [0.21, 0.39]	1289.01	6.51	< .001

H3 statistical models

Table S3 reports the full statistical models for the analyses testing H3 in the main manuscript (reported in Table 2).

Table S3
Results from the models testing H3

Study	Sharing Type	Term	β [95% CI]	*df*	*t*	*p*
Study 1	broadcast sharing	intercept (control)	-0.21 [-0.29, -0.14]	141.81	5.73	< .001
		other - control	0.47 [0.37, 0.57]	1611.45	9.03	< .001
		self - control	0.41 [0.31, 0.51]	1610.51	7.88	< .001
	narrowcast sharing	intercept (control)	-0.19 [-0.27, -0.11]	90.61	4.72	< .001
		other - control	0.44 [0.34, 0.54]	1612.30	8.65	< .001
		self - control	0.33 [0.23, 0.42]	1611.13	6.48	< .001
Study 2	broadcast sharing	intercept (control)	-0.02 [-0.11, 0.07]	549.69	0.50	.617
		other - control	0.03 [-0.02, 0.08]	2890.52	1.14	.253
		self - control	0.04 [-0.01, 0.09]	2899.11	1.72	.086
	narrowcast	intercept (control)	-0.03 [-0.12, 0.05]	568.79	0.75	.454

	sharing	other - control	0.12 [0.06, 0.17]	2895.02	4.18	< .001
		self - control	0.09 [0.04, 0.15]	2903.02	3.26	.001
Study 3	narrowcast sharing	intercept (control)	0.03 [-0.07, 0.13]	192.66	0.66	.512
		other - control	-0.04 [-0.10, 0.02]	5855.96	1.42	.155
		self - control	-0.05 [-0.11, 0.01]	5854.22	1.74	.082
Study 4	broadcast sharing	intercept (control)	-0.12 [-0.28, 0.03]	142.84	1.55	.124
		other - control	0.21 [0.14, 0.28]	1292.54	6.17	< .001
		self - control	0.17 [0.11, 0.24]	1295.59	5.17	< .001
	narrowcast sharing	intercept (control)	-0.23 [-0.37, -0.08]	167.43	3.08	.002
		other - control	0.41 [0.32, 0.50]	1292.44	9.42	< .001
		self - control	0.26 [0.18, 0.35]	1295.34	6.06	< .001

Word count

Table S4 reports the full statistical models for the word count analyses described in the main manuscript.

Table S4

Results from the models testing relationships with word count

Dependent variable	Sharing Type	Term	β [95% CI]	*df*	*t*	*p*
Self-relevance	study 1	intercept	0.22 [0.13, 0.31]	42.59	5.00	< .001
		word count	0.01 [0.00, 0.01]	183.79	5.78	< .001
	study 2	intercept	0.03 [-0.05, 0.11]	247.93	0.70	.483
		word count	0.01 [0.01, 0.01]	217.44	5.85	< .001
	study 4	intercept	0.01 [-0.12, 0.13]	156.54	0.11	.916
		word count	0.01 [0.01, 0.02]	73.01	3.73	< .001
Social relevance	study 1	intercept	0.21 [0.12, 0.30]	46.25	4.87	< .001
		word count	0.01 [0.00, 0.01]	166.97	4.41	< .001
	study 2	intercept	0.03 [-0.05, 0.11]	295.59	0.83	.408
		word count	0.01 [0.00, 0.01]	251.77	4.65	< .001
	study 4	intercept	0.01 [-0.12, 0.14]	135.53	0.12	.904
		word count	0.01 [0.01, 0.02]	82.37	4.04	< .001
Broadcast sharing intention	study 1	intercept	0.23 [0.15, 0.30]	146.18	5.92	< .001
		word count	0.00 [0.00, 0.01]	240.13	3.31	.001
	study 2	intercept	-0.00 [-0.09, 0.08]	438.46	0.08	.933
		word count	0.00 [0.00, 0.01]	232.59	2.46	.015
	study 4	intercept	0.01 [-0.15, 0.16]	125.75	0.08	.940
		word count	0.01 [0.00, 0.01]	62.60	2.40	.020
Narrowcast sharing intention	study 1	intercept	0.20 [0.12, 0.27]	118.01	5.16	< .001
		word count	0.01 [0.00, 0.01]	265.66	3.90	< .001
	study 2	intercept	0.03 [-0.05, 0.11]	424.76	0.77	.441
		word count	0.00 [0.00, 0.01]	212.59	2.67	.008
	study 4	intercept	0.01 [-0.13, 0.14]	130.20	0.13	.895
		word count	0.01 [0.00, 0.02]	56.04	2.69	.010

News topic models

Table S5-6 reports the full statistical models for the news topic moderation analyses described in the main manuscript.

Main effects. Compared to climate articles, health articles tended to be rated as being more socially relevant, elicited stronger activity in the self-referential and social cognitive ROIs, and were associated with higher intentions to share directly with others (narrowcast sharing) but lower intentions to share on social media (broadcast sharing).

Interactions. With respect to moderation of the hypothetical relationships of interest (H1-6), we did not observe consistent moderating effects of article topic across hypotheses. The correlational relationship between self-relevance and broadcast sharing tended to be stronger for climate compared to health articles, whereas the relationship between social relevance and narrowcast sharing tended to be stronger for health compared to climate articles. The correlational relationships between ROIs and relevance and sharing (H4-5) were not moderated by article topic. The effects of the interventions on relevance (H2), sharing (H3), and ROI activity (H6) were not consistently moderated by article topic.

This overall pattern suggests that although there are mean-level differences between climate and health news articles in perceptions of relevance, brain activity, and sharing intentions, individuals tend to consider both self and social relevance when making decisions to share and the interventions tended to be equally effective across article topics.

Table S5

Results from the models testing hypotheses H1-3 exploring news topic as a moderator

Dependent variable	Parameter	β [95% CI]		
		Study 2	Study 3	Study 4
H1a-b: Broadcast sharing intention	topic (health)	**-0.04 [-0.08, -0.01]**	—	**-0.06 [-0.12, -0.01]**
	self-relevance	0.25 [0.19, 0.31]	—	0.20 [0.12, 0.28]
	self-relevance x topic (health)	**-0.06 [-0.12, -0.00]**	—	-0.08 [-0.16, 0.01]
	social relevance	0.19 [0.14, 0.25]	—	0.22 [0.13, 0.30]
	social relevance x topic (health)	0.03 [-0.03, 0.09]	—	0.01 [-0.07, 0.09]
H1a-b: Narrowcast sharing intention	topic (health)	**0.09 [0.05, 0.13]**	**0.14 [0.07, 0.22]**	**0.09 [0.02, 0.16]**
	self-relevance	0.12 [0.06, 0.18]	0.28 [0.23, 0.33]	0.02 [-0.06, 0.11]
	self-relevance x topic (health)	-0.05 [-0.12, 0.02]	0.03 [-0.03, 0.09]	0.06 [-0.04, 0.16]
	social relevance	0.31 [0.25, 0.36]	0.18 [0.12, 0.24]	0.52 [0.44, 0.60]
	social relevance x topic (health)	**0.08 [0.01, 0.15]**	**0.06 [0.01, 0.12]**	0.03 [-0.07, 0.13]
H2a: Self-relevance	topic (health)	**-0.16 [-0.31, -0.01]**	**0.22 [0.07, 0.37]**	-0.04 [-0.22, 0.13]
	other - control	0.01 [-0.09, 0.11]	0.03 [-0.05, 0.11]	0.18 [0.04, 0.32]
	other - control x topic (health)	0.09 [-0.05, 0.24]	-0.07 [-0.18, 0.04]	-0.12 [-0.32, 0.07]
	self - control	0.26 [0.16, 0.36]	0.10 [0.03, 0.18]	0.41 [0.27, 0.54]
	self - control x topic (health)	-0.03 [-0.17, 0.12]	**-0.16 [-0.26, -0.05]**	0.03 [-0.16, 0.23]
H2b: Social relevance	topic (health)	0.09 [-0.05, 0.23]	**0.31 [0.18, 0.45]**	**0.21 [0.07, 0.36]**
	other - control	0.16 [0.06, 0.26]	0.02 [-0.06, 0.10]	0.48 [0.35, 0.61]
	other - control x topic (health)	0.05 [-0.10, 0.19]	0.03 [-0.07, 0.14]	-0.11 [-0.30, 0.08]
	self - control	0.20 [0.10, 0.29]	0.07 [-0.01, 0.14]	0.41 [0.28, 0.54]
	self - control x topic (health)	-0.12 [-0.26, 0.02]	-0.05 [-0.16, 0.05]	**-0.23 [-0.41, -0.04]**
	topic (health)	-0.08 [-0.16, 0.01]	—	-0.08 [-0.19, 0.02]

H3a: Broadcast sharing intention	other - control	0.03 [-0.05, 0.10]	—	0.16 [0.06, 0.26]
	other - control x topic (health)	0.00 [-0.10, 0.11]	—	0.10 [-0.04, 0.24]
	self - control	0.05 [-0.03, 0.12]	—	0.21 [0.11, 0.30]
	self - control x topic (health)	-0.01 [-0.12, 0.10]	—	-0.06 [-0.20, 0.07]
H3b: Narrowcast sharing intention	topic (health)	0.07 [-0.02, 0.16]	**0.23 [0.09, 0.36]**	0.12 [-0.01, 0.25]
	other - control	0.08 [-0.00, 0.16]	-0.06 [-0.14, 0.02]	0.37 [0.25, 0.49]
	other - control x topic (health)	0.07 [-0.05, 0.19]	0.04 [-0.07, 0.15]	0.07 [-0.11, 0.25]
	self - control	0.08 [0.00, 0.17]	-0.05 [-0.13, 0.03]	0.27 [0.15, 0.39]
	self - control x topic (health)	0.01 [-0.11, 0.13]	-0.00 [-0.12, 0.11]	-0.02 [-0.19, 0.16]

Note. Parameter estimates for models with sharing behavior as the dependent variable are log odds. All statistics from each model is reported in Supplementary Material. Climate articles are the reference group for topic. Statistically significant relationships with topic are bolded.

Table S6

Results from Study 3 models testing hypotheses H4-6 exploring news topic as a moderator

Dependent variable	Term	β [95% CI]	*df*	*t*	*p*
H4b: Self-relevance	intercept	-0.08 [-0.15, 0.00]	101.83	1.88	.063
	topic (health)	**0.14 [0.09, 0.18]**	**5923.21**	**5.52**	**< .001**
	self-referential ROI	0.03 [0.00, 0.07]	250.16	1.97	.050
	self-referential ROI x topic (health)	0.02 [-0.02, 0.06]	5883.47	0.92	.355
H4b: Social relevance	intercept	-0.17 [-0.26, -0.08]	97.93	3.69	< .001
	topic (health)	**0.30 [0.25, 0.35]**	**5924.99**	**12.18**	**< .001**
	social cognitive ROI	0.04 [0.00, 0.07]	226.6	2.16	.032
	social cognitive ROI x topic (health)	0.01 [-0.03, 0.06]	5903.41	0.66	.512
H5a: Narrowcast sharing intention	intercept	-0.13 [-0.20, -0.05]	103.54	3.25	.002
	topic (health)	**0.24 [0.19, 0.28]**	**5845.6**	**9.56**	**< .001**
	self-referential ROI	0.07 [0.04, 0.11]	241.01	4.18	< .001
	self-referential ROI x topic (health)	0.01 [-0.04, 0.05]	5837.06	0.31	.759
H5b: Narrowcast sharing intention	intercept	-0.14 [-0.22, -0.07]	105.8	3.65	< .001
	topic (health)	**0.24 [0.19, 0.29]**	**5840.93**	**9.37**	**< .001**
	social cognitive ROI	0.07 [0.04, 0.11]	240.64	4.31	< .001
	social cognitive ROI x topic (health)	-0.01 [-0.06, 0.03]	5824.61	0.51	.607
H6a: Self-referential ROI	Intercept (control)	0.01 [-0.11, 0.13]	111.15	0.23	.817
	topic (health)	**0.14 [0.05, 0.23]**	**5759.54**	**3.14**	**.002**
	other - control	0.09 [-0.01, 0.19]	223.56	1.76	.080
	other - control x topic (health)	-0.01 [-0.13, 0.12]	5759.09	0.10	.923
	self - control	0.13 [0.02, 0.23]	194.4	2.38	.018
	self - control x topic (health)	-0.08 [-0.20, 0.05]	5759.09	1.23	.219
H6b: Social cognitive ROI	Intercept (control)	0.27 [0.15, 0.39]	112.87	4.55	< .001
	topic (health)	**0.11 [0.03, 0.20]**	**5759.59**	**2.58**	**.010**
	other - control	0.06 [-0.04, 0.15]	233.74	1.16	.249
	other - control x topic (health)	0.01 [-0.12, 0.13]	5759.16	0.09	.929
	self - control	0.10 [-0.00, 0.20]	198.59	1.91	.057
	self - control x topic (health)	-0.06 [-0.18, 0.07]	5759.1	0.89	.371

Note. Climate articles are the reference group for topic. Statistically significant relationships with topic are bolded. Degrees of freedom were calculated using the Satterthwaite approximation.

Culture models

Table S7 reports the full statistical models for the cultural moderation analyses described in the main manuscript.

Table S7

Results from the models assessing moderation by cultural context

Dependent variable	Term	*β* [95% CI]	*df*	*t*	*p*
H1a-b: Narrowcast sharing intention	intercept	-0.03 [-0.11, 0.04]	82.76	0.89	.377
	sample (USA)	0.09 [-0.01, 0.20]	82.28	1.78	.078
	self-relevance	0.32 [0.26, 0.38]	89.64	11.01	< .001
	self-relevance x sample (USA)	-0.03 [-0.11, 0.04]	84.71	0.87	.385
	social relevance	0.22 [0.14, 0.29]	88.54	5.95	< .001
	social relevance x sample (USA)	0.04 [-0.06, 0.14]	82.51	0.79	.429
H2a: Self-relevance	intercept (control)	0.01 [-0.11, 0.13]	121.34	0.22	.827
	sample (USA)	-0.05 [-0.21, 0.12]	121.28	0.58	.560
	other - control	0.04 [-0.05, 0.12]	5925.43	0.83	.409
	other x sample (USA)	-0.06 [-0.17, 0.06]	5925.30	0.94	.347
	self - control	0.04 [-0.05, 0.12]	5925.22	0.89	.372
	self - control x sample (USA)	-0.01 [-0.13, 0.11]	5925.33	0.20	.843
H2b: Social relevance	intercept (control)	0.06 [-0.07, 0.19]	111.11	0.87	.388
	sample (USA)	-0.17 [-0.35, 0.02]	111.07	1.81	.074
	other - control	0.02 [-0.07, 0.10]	5925.36	0.39	.694
	other x sample (USA)	0.06 [-0.06, 0.17]	5925.26	0.99	.321
	self - control	0.00 [-0.08, 0.08]	5925.20	0.00	1.000
	self - control x sample (USA)	0.09 [-0.03, 0.20]	5925.28	1.52	.128
H3: Narrowcast sharing intention	intercept (control)	-0.00 [-0.12, 0.12]	124.80	0.04	.969
	sample (USA)	0.06 [-0.10, 0.22]	124.32	0.70	.483
	other - control	-0.01 [-0.10, 0.07]	5846.72	0.26	.792
	other x sample (USA)	-0.04 [-0.16, 0.08]	5846.55	0.63	.528
	self - control	-0.05 [-0.13, 0.04]	5846.54	1.07	.283
	self - control x sample (USA)	0.01 [-0.11, 0.13]	5846.55	0.11	.909
H4b: Self-relevance	intercept	0.04 [-0.07, 0.15]	82.64	0.74	.464
	sample (USA)	-0.09 [-0.24, 0.06]	83.66	1.21	.229
	self-referential	0.04 [0.00, 0.08]	84.47	2.23	.028
	self-referential x sample (USA)	0.01 [-0.04, 0.06]	82.89	0.42	.673
H4b: Social relevance	intercept	0.06 [-0.07, 0.18]	81.87	0.88	.381
	sample (USA)	-0.14 [-0.31, 0.03]	83.42	1.61	.111
	social cognitive	0.05 [0.01, 0.09]	83.25	2.42	.018
	social cognitive x sample (USA)	0.01 [-0.05, 0.06]	82.63	0.29	.772
H5a: Narrowcast sharing intention	intercept	-0.02 [-0.13, 0.09]	82.89	0.31	.754
	sample (USA)	0.01 [-0.14, 0.16]	83.88	0.09	.928
	self-referential	0.06 [0.02, 0.10]	82.76	3.10	.003
	self-referential x sample (USA)	0.04 [-0.01, 0.09]	81.13	1.51	.135
H5b: Narrowcast sharing intention	intercept	-0.03 [-0.14, 0.08]	82.49	0.61	.544
	sample (USA)	0.01 [-0.14, 0.16]	84.55	0.17	.865
	social cognitive	0.06 [0.02, 0.10]	82.57	3.10	.003
	social cognitive x sample (USA)	0.02 [-0.03, 0.08]	81.34	0.87	.389
H6a: Self-referential ROI	intercept (control)	-0.14 [-0.29, 0.01]	83.01	1.87	.064
	sample (USA)	**0.43 [0.22, 0.63]**	**82.99**	**4.08**	**< .001**

	other - control	0.10 [-0.01, 0.22]	82.72	1.81	.074
	other x sample (USA)	-0.03 [-0.19, 0.12]	82.55	0.44	.663
	self - control	0.08 [-0.05, 0.20]	82.60	1.23	.222
	self - control x sample (USA)	0.02 [-0.15, 0.19]	82.68	0.24	.814
H6b: Social cognitive ROI	intercept (control)	0.12 [-0.03, 0.27]	83.11	1.66	.102
	sample (USA)	**0.38 [0.18, 0.59]**	**83.09**	**3.73**	**< .001**
	other - control	0.11 [0.00, 0.22]	82.55	2.01	.047
	other x sample (USA)	-0.10 [-0.25, 0.05]	82.37	1.27	.208
	self - control	0.07 [-0.06, 0.19]	82.65	1.10	.276
	self - control x sample (USA)	0.01 [-0.16, 0.18]	82.73	0.11	.915

Note. The reference group is the Dutch cohort. USA = American cohort. Statistically significant cultural context effects are bolded.

Climate action models

Table S8 reports pairwise contrasts of perceived environmental impact for each action category separately.

Table S8

Results from Study 1 models exploring downstream impacts on climate attitudes, beliefs, and intentions

Dependent variable	Term	*β* [95% CI]	*df*	*t*	*p*
Petition broadcast sharing intention	intercept (control)	-0.09 [-0.17, -0.02]	918.6	2.52	.012
	other - control	0.21 [0.08, 0.35]	918.6	3.21	< .001
	self - control	0.18 [0.05, 0.31]	918.6	2.68	.007
Petition narrowcast sharing intention	intercept (control)	-0.07 [-0.14, 0.00]	908.23	1.86	.063
	other - control	0.18 [0.05, 0.31]	908.18	2.74	.006
	self - control	0.11 [-0.02, 0.23]	908.18	1.61	.108
Climate change knowledge	intercept (control)	-0.10 [-0.17, -0.03]	1610	2.87	.004
	other - control	0.22 [0.10, 0.34]	1610	3.52	< .001
	self - control	0.20 [0.08, 0.32]	1610	3.26	< .001
Climate change self-efficacy	intercept (control)	-0.04 [-0.11, 0.03]	1610	1.19	.235
	other - control	0.13 [0.01, 0.25]	1610	2.13	.034
	self - control	0.04 [-0.08, 0.16]	1610	0.66	.511
Perceived environmental impact	intercept (control)	-0.06 [-0.11, -0.01]	1610.02	2.27	.023
	other - control	0.17 [0.08, 0.26]	1610.01	3.77	< .001
	self - control	0.07 [-0.02, 0.16]	1610.01	1.60	.110

Note. Degrees of freedom in the petition and perceived environmental impact models were calculated using the Satterthwaite approximation.

Table S9

Pairwise contrasts by climate action category

Category	Contrast	*β* [95% CI]	*df*	*t*	*p*
Collective	other - control	0.15 [0.06, 0.25]	2152.58	3.19	.001
	self - control	0.09 [-0.01, 0.18]	2152.58	1.78	.075
Conversations	other - control	0.13 [0.01, 0.25]	5252.29	2.10	.036
	self - control	0.12 [-0.00, 0.24]	5252.29	1.93	.053
Diet	other - control	0.19 [0.09, 0.29]	2448.9	3.81	< .001
	self - control	0.07 [-0.03, 0.17]	2448.9	1.45	.147
Energy	other - control	0.18 [0.06, 0.30]	5252.29	3.00	.003

	self - control	0.08 [-0.04, 0.20]	5252.29	1.35	.178
Recycle	other - control	0.18 [0.06, 0.30]	5252.29	2.92	.004
	self - control	0.11 [-0.01, 0.23]	5252.29	1.79	.074
Transit	other - control	0.18 [0.07, 0.28]	3085.08	3.34	< .001
	self - control	-0.01 [-0.11, 0.10]	3085.08	0.10	.923

Parallel mediation analyses

We used Bayesian multilevel mediation to test the degree to which the effect of the interventions (self-focused v. control, or other-focused v. control) on sharing intentions occurred indirectly through self and social relevance. We fit models separately for broad- and narrowcast sharing intentions. Self and social relevance were included as parallel mediators and we jointly fit three models regressing 1) self-relevance on intervention condition, 2) social relevance on intervention condition, and 3) sharing intention on intervention condition, self-relevance, and social relevance. In within-person models (Studies 2-4), intercepts and intervention condition were allowed to vary randomly across people in all three models, and self and social relevance were also allowed to vary randomly in the third model with sharing intentions as the outcome. In between-person models (Study 1), intercepts were allowed to vary randomly across people in all three models, and self and social relevance were also allowed to vary randomly in the third model with sharing intentions as the outcome. The mediation models were estimated using the *brm* function from the *brms* package (Bürkner, 2017) in R with the same weakly informed prior used in the models reported in the main manuscript. Indirect effects were calculated as a*b + cov(a, b) in within-person models (Studies 2-4) and a*b in between-person models (Study 1). Intervals around the path estimates are 95% credibility intervals from the posterior distribution. As outlined in our preregistration, indirect effects were interpreted to be present if the 95% credible intervals did not contain zero.

In Studies 1 and 4, we generally replicate our prior research (Cosme et al., 2022) showing that for both intervention conditions, there are indirect pathways through both self and social relevance. However, in the studies that had weaker intervention effects on sharing to begin with (Studies 2-3), we did not generally observe indirect effects through self or social relevance.

Table S10
Results from Bayesian multilevel parallel mediation models

Model	Intervention	Path	*Mdn* [95% CrI]			
			Study 1	Study 2	Study 3	Study 4
Broadcast sharing intention	Self-focused v. control	a1: intervention → self-relevance	0.35 [0.26, 0.44]	0.23 [0.14, 0.32]	—	0.42 [0.30, 0.55]
		b1: self-relevance → sharing	0.23 [0.19, 0.26]	0.22 [0.18, 0.27]	—	0.16 [0.09, 0.23]
		a1b1: intervention → self-relevance → sharing	**0.08 [0.06, 0.11]**	0.04 [0.00, 0.09]	—	**0.08 [0.03, 0.13]**
		a2: intervention → social relevance	0.30 [0.20, 0.39]	0.13 [0.04, 0.22]	—	0.31 [0.18, 0.43]
		b2: social relevance → sharing	0.16 [0.13, 0.20]	0.19 [0.15, 0.24]	—	0.19 [0.11, 0.26]

		a2b2: intervention → social relevance → sharing	**0.05 [0.03, 0.07]**	0.02 [-0.02, 0.06]	—	**0.07 [0.02, 0.12]**
		c: total (indirect + direct) effect	0.33 [0.24, 0.41]	0.05 [0.00, 0.10]	—	0.14 [0.07, 0.23]
		c': direct effect	0.20 [0.13, 0.27]	-0.03 [-0.07, 0.01]	—	0.02 [-0.05, 0.09]
Narrowcast sharing intention	Self-focused v. control	a1: intervention → self-relevance	0.37 [0.27, 0.46]	0.23 [0.14, 0.32]	0.03 [-0.04, 0.10]	0.42 [0.29, 0.54]
		b1: self-relevance → sharing	0.24 [0.19, 0.28]	0.12 [0.07, 0.17]	0.36 [0.31, 0.41]	0.13 [0.05, 0.21]
		a1b1: intervention → self-relevance → sharing	**0.09 [0.06, 0.12]**	0.01 [-0.03, 0.05]	0.01 [-0.01, 0.04]	**0.07 [0.02, 0.13]**
		a2: intervention → social relevance	0.31 [0.22, 0.40]	0.13 [0.05, 0.22]	0.05 [-0.01, 0.11]	0.30 [0.18, 0.42]
		b2: social relevance → sharing	0.27 [0.23, 0.31]	0.37 [0.32, 0.42]	0.18 [0.13, 0.23]	0.42 [0.33, 0.51]
		a2b2: intervention → social relevance → sharing	**0.08 [0.06, 0.11]**	0.04 [-0.01, 0.09]	0.01 [-0.01, 0.02]	**0.13 [0.07, 0.21]**
		c: total (indirect + direct) effect	0.30 [0.21, 0.39]	0.12 [0.06, 0.18]	-0.05 [-0.11, 0.01]	0.24 [0.13, 0.35]
		c': direct effect	0.13 [0.06, 0.20]	0.04 [-0.01, 0.09]	-0.07 [-0.12, -0.02]	0.06 [-0.03, 0.14]
Broadcast sharing intention	Other-focused v. control	a1: intervention → self-relevance	0.42 [0.32, 0.50]	0.03 [-0.05, 0.11]	—	0.12 [0.00, 0.24]
		b1: self-relevance → sharing	0.22 [0.18, 0.25]	0.21 [0.16, 0.26]	—	0.16 [0.08, 0.24]
		a1b1: intervention → self-relevance → sharing	**0.09 [0.06, 0.12]**	0.01 [-0.02, 0.04]	—	0.04 [0.00, 0.09]
		a2: intervention → social relevance	0.44 [0.35, 0.53]	0.16 [0.09, 0.24]	—	0.44 [0.32, 0.56]
		b2: social relevance → sharing	0.18 [0.14, 0.22]	0.19 [0.14, 0.24]	—	0.19 [0.12, 0.27]
		a2b2: intervention → social relevance → sharing	**0.08 [0.06, 0.11]**	0.01 [-0.02, 0.04]	—	**0.07 [0.03, 0.13]**
		c: total (indirect + direct) effect	0.36 [0.28, 0.45]	0.04 [-0.01, 0.09]	—	0.19 [0.12, 0.26]
		c': direct effect	0.19 [0.12, 0.26]	0.00 [-0.04, 0.05]	—	0.09 [0.02, 0.15]

Narrowcast sharing intention	Other-focused v. control	a1: intervention → self-relevance	0.45 [0.36, 0.54]	0.02 [-0.06, 0.10]	0.00 [-0.06, 0.07]	0.12 [-0.01, 0.23]
		b1: self-relevance → sharing	0.21 [0.17, 0.25]	0.09 [0.04, 0.14]	0.25 [0.20, 0.29]	0.02 [-0.06, 0.09]
		a1b1: intervention → self-relevance → sharing	**0.09 [0.07, 0.12]**	-0.01 [-0.04, 0.02]	0.00 [-0.02, 0.02]	-0.01 [-0.05, 0.02]
		a2: intervention → social relevance	0.47 [0.38, 0.56]	0.16 [0.08, 0.23]	0.05 [-0.02, 0.11]	0.44 [0.31, 0.56]
		b2: social relevance → sharing	0.29 [0.24, 0.32]	0.38 [0.33, 0.44]	0.27 [0.22, 0.33]	0.52 [0.43, 0.61]
		a2b2: intervention → social relevance → sharing	**0.13 [0.10, 0.17]**	**0.07 [0.02, 0.11]**	0.01 [-0.01, 0.04]	**0.24 [0.16, 0.34]**
		c: total (indirect + direct) effect	0.41 [0.31, 0.50]	0.11 [0.06, 0.17]	-0.04 [-0.10, 0.02]	0.41 [0.31, 0.50]
		c': direct effect	0.18 [0.11, 0.25]	0.05 [0.00, 0.09]	-0.05 [-0.10, -0.00]	0.18 [0.11, 0.25]

Note. Paths with 95% credible intervals that do not include zero are bolded.

Table S11

Percent of the total effect mediated by self and social relevance in models with 95% credible intervals that did not contain zero

Model	Intervention	Path	*% of total effect mediated*			
			Study 1	Study 2	Study 3	Study 4
Broadcast sharing intention	Self-focused v. control	Self-relevance	24	—	—	57
		Social relevance	15	—	—	46
Narrowcast sharing intention	Self-focused v. control	Self-relevance	29	—	—	28
		Social relevance	27	—	—	56
Broadcast sharing intention	Other-focused v. control	Self-relevance	25	—	—	—
		Social relevance	22	—	—	39
Narrowcast sharing intention	Other-focused v. control	Self-relevance	23	—	—	—
		Social relevance	33	61	—	60

We fit similar mediation models in the Study 3 data replacing self-reported relevance with ROI activity. We deviated from our preregistered analysis plan to consider both ROIs simultaneously and match the parallel mediation analyses reported above. Mirroring the self-reported relevance results, there were no indirect effects for through ROI activity (Table S12).

Table S12
Results from Bayesian multilevel parallel mediation models with ROIs as mediators in Study 3

Model	Intervention	Path	*Mdn* [95% CrI]
Narrowcast sharing intention	Self- focused v. control	a1: intervention → self-referential ROI	0.10 [0.00, 0.19]
		b1: self-referential ROI → sharing	0.10 [0.02, 0.18]
		a1b1: intervention → self-referential ROI → sharing	0.01 [0.00, 0.03]
		a2: intervention → social cognitive ROI	0.08 [-0.01, 0.18]
		b2: social cognitive ROI → sharing	-0.02 [-0.10, 0.06]
		a2b2: intervention → social cognitive ROI → sharing	0.00 [-0.01, 0.02]
		c: total (indirect + direct) effect	-0.05 [-0.11, 0.01]
		c': direct effect	-0.06 [-0.12, 0.00]
Narrowcast sharing intention	Other- focused v. control	a1: intervention → self-referential ROI	0.09 [0.00, 0.17]
		b1: self-referential ROI → sharing	0.11 [0.02, 0.19]
		a1b1: intervention → self-referential ROI → sharing	0.01 [0.00, 0.03]
		a2: intervention → social cognitive ROI	0.06 [-0.02, 0.14]
		b2: social cognitive ROI → sharing	-0.02 [-0.10, 0.07]
		a2b2: intervention → social cognitive ROI → sharing	0.00 [-0.01, 0.01]
		c: total (indirect + direct) effect	-0.03 [-0.10, 0.03]
		c': direct effect	-0.04 [-0.11, 0.02]

Note. Paths with 95% credible intervals that do not include zero are bolded.

Study 3 analyses

Sensitivity analyses

Given the very high correlations between the preregistered ROIs reported in the main manuscript (r = .94, 95% CI [.94, .94]), we conducted sensitivity analyses using alternative ROIs. These ROIs were defined using the ROI masks from Scholz et al. (2017). However, there were overlapping clusters in precuneus and posterior cingulate cortex between the self-referential and social cognitive ROIs. To create non-overlapping ROIs, we removed this cluster from the social cognitive ROI. Activity in these alternative ROIs were less highly correlated within-person (r = .56, 95% CI [.54, .58]). Nonetheless, we replicate the results reported in the main manuscript with these ROIs. Full results are reported in Table S13.

Table S13
Results from the models using alternatively defined ROIs

Dependent variable	Term	β [95% CI]	*df*	*t*	*p*
H4a: Self-relevance	intercept	-0.01 [-0.09, 0.07]	84.62	0.26	.794
	self-referential ROI	0.03 [0.01, 0.06]	83.66	2.40	.018
H4b: Social relevance	intercept	-0.01 [-0.09, 0.08]	84.07	0.19	.847
	social cognitive ROI	0.04 [0.01, 0.06]	82.98	2.86	.005
H5a: Narrowcast sharing intention	intercept	-0.02 [-0.09, 0.06]	85.08	0.45	.651
	self-referential ROI	0.06 [0.03, 0.09]	83.56	4.40	< .001
H5b: Narrowcast sharing intention	intercept	-0.01 [-0.08, 0.06]	84.71	0.26	.797
	social cognitive ROI	0.04 [0.02, 0.07]	83.49	3.41	.001
H6a: Self-referential ROI	intercept (control)	0.23 [0.12, 0.33]	84.12	4.38	< .001
	other - control	0.11 [0.03, 0.19]	84.42	2.86	.005

	self - control	0.13 [0.04, 0.21]	83.69	2.84	.006
H6b: Social cognitive ROI	intercept (control)	0.27 [0.15, 0.39]	84.19	4.58	< .001
	other - control	0.01 [-0.07, 0.08]	83.16	0.21	.837
	self - control	0.05 [-0.04, 0.13]	84.03	1.11	.271

Whole-brain analyses

We complemented the preregistered ROI analyses with whole-brian univariate analyses. First-level (i.e., participant-specific) statistical analyses were conducted in MNI space in SPM12 (Wellcome Department of Cognitive Neurology; http://www.fil.ion.ucl.ac.uk/spm) using nipype (Gorgolewski et al., 2011). Event-related condition effects were estimated using a fixed-effects general linear model and convolving the canonical hemodynamic response function with stimulus events. Separate regressors were entered for conditions of interest (Self-focused, Other-focused, Control) and event duration was defined as the duration of the news presentation. Block instructions and ratings were included as regressors of no interest. We also included the following regressors to account for motion: absolute displacement from the origin in Euclidean distance and the displacement derivative for both translation and rotation, dummy-coded motion artifact outliers (defined as framewise displacement > .75mm), and cerebrospinal fluid average signals. All data were high-pass filtered at 128 s, and temporal autocorrelation was modeled using FAST. Linear contrasts for each condition of interest versus the implicit baseline (“rest”) were estimated for each participant and used as inputs in second-level analyses.

A series of pairwise t-tests were used to estimate second-level random effects. Specifically, we computed the following contrasts using the first-level participant images as inputs: Self-focused > Control, Other-focused > Control, Self-focused + Other-focused > Control, Self-focused > Other-focused. Results for the primary contrasts of interest are visualized in Figure S3. All unthresholded maps are available on NeuroVault (https://neurovault.org/collections/EASIASFI).

H5 models including self-reported relevance and ROI activity

We tested whether the self-reported and ROI indices of self and social motives explained unique variance in news sharing. Compared to models that either included relevance ratings or ROI activity alone, the best fitting self and social models included both self-reported and ROI indicators of self and social motives (Table S14). Within each model, both self-reported relevance ratings and ROI activity remained statistically significant predictors of news sharing intentions (Table S15). This demonstrates that they account for unique variance and that including both subjective and objective measures of self and social motives increases the ability to explain news sharing intentions.

Table S14
Model comparison

Model	Indices included	AIC	χ2	*df*	*p*
Self	self-referential ROI	16364.80			
	self-relevance rating	14930.55	1434.25	0	
	self-referential ROI + self-relevance	14908.82	29.74	4	< 0.001
Social	social cognitive ROI	16375.31			
	social relevance rating	15080.92	1294.40	0	
	social cognitive ROI + social relevance	15068.54	20.38	4	< 0.001

Table S15

Combined models testing hypothesis H5

Dependent variable	Term	*β [95% CI]*	*df*	*t*	*p*
H5a: Narrowcast sharing intention	intercept	0.00 [-0.05, 0.06]	83.16	0.11	.913
	self-referential ROI	0.06 [0.03, 0.08]	81.24	5.00	< .001
	self-relevance rating	0.46 [0.42, 0.49]	78.17	26.21	< .001
H5b: Narrowcast sharing intention	intercept	0.00 [-0.06, 0.06]	86.06	0.11	.912
	social cognitive ROI	0.05 [0.03, 0.07]	4336.61	4.49	< .001
	social relevance rating	0.43 [0.39, 0.47]	81.49	20.32	< .001

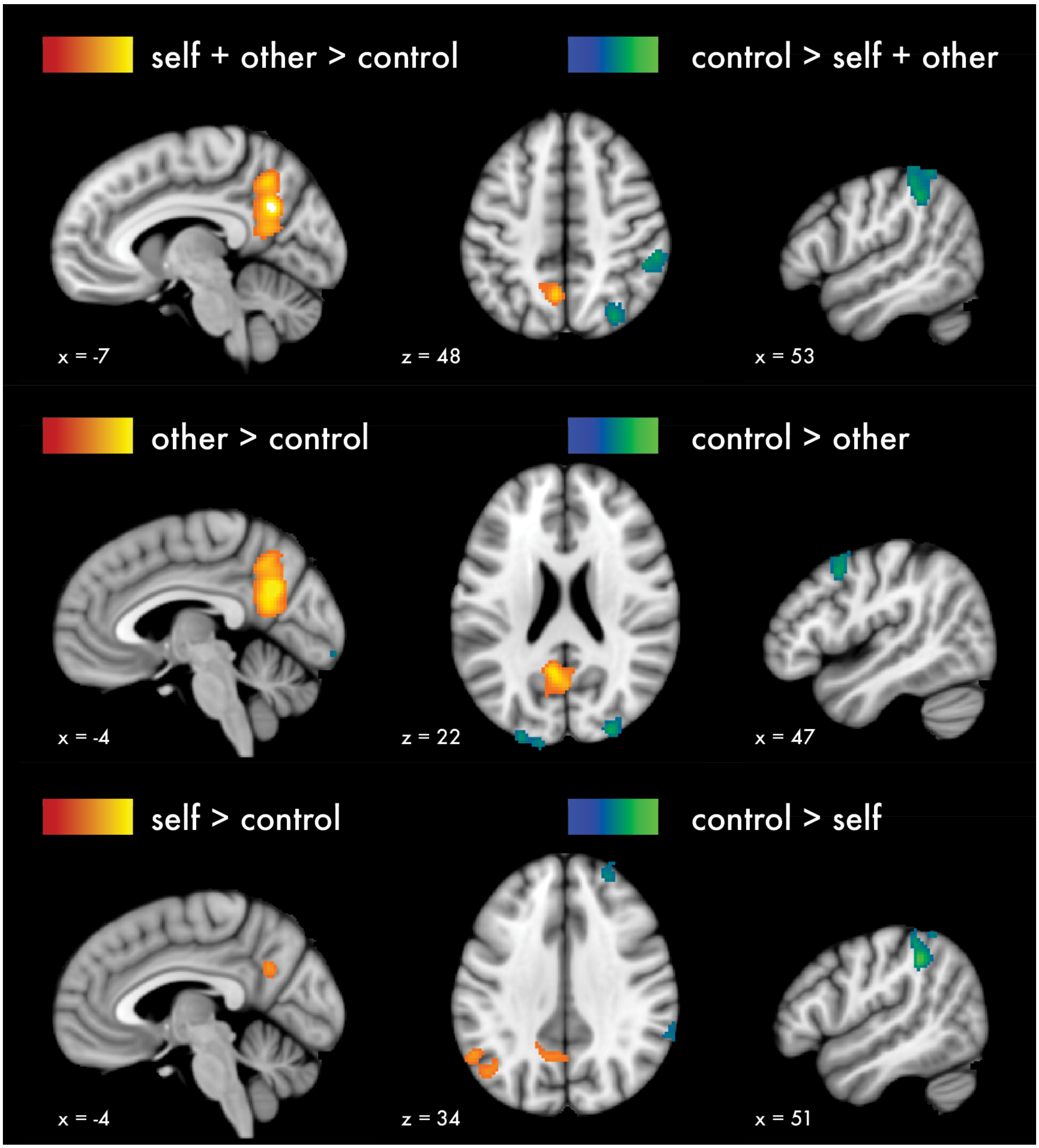

Figure S3. Univariate contrasts. Results are thresholded at *p* < .005 and *k* = 150 for visualization purposes (i.e., this threshold is not corrected for multiple comparisons). Cluster extent (*k*) is measured in 2 x 2 x 2 mm voxels.

Study 4 between-group analysis

Given that the MRI-adapted content-framing interventions in Study 3 were less effective, Study 4 examined how different factors affecting engagement (reflecting versus writing comments, and the amount of reflection time allowed—12s versus unlimited time) impacted intervention effectiveness. Consistent with the findings from the prior studies, participants who were randomly assigned to complete the content-framing intervention by writing comments (as in Studies 1-2) rated health and climate news articles are more self and socially relevant, and reported higher intentions to share them compared to participants who reflected by did not write comments (as in Study 3).

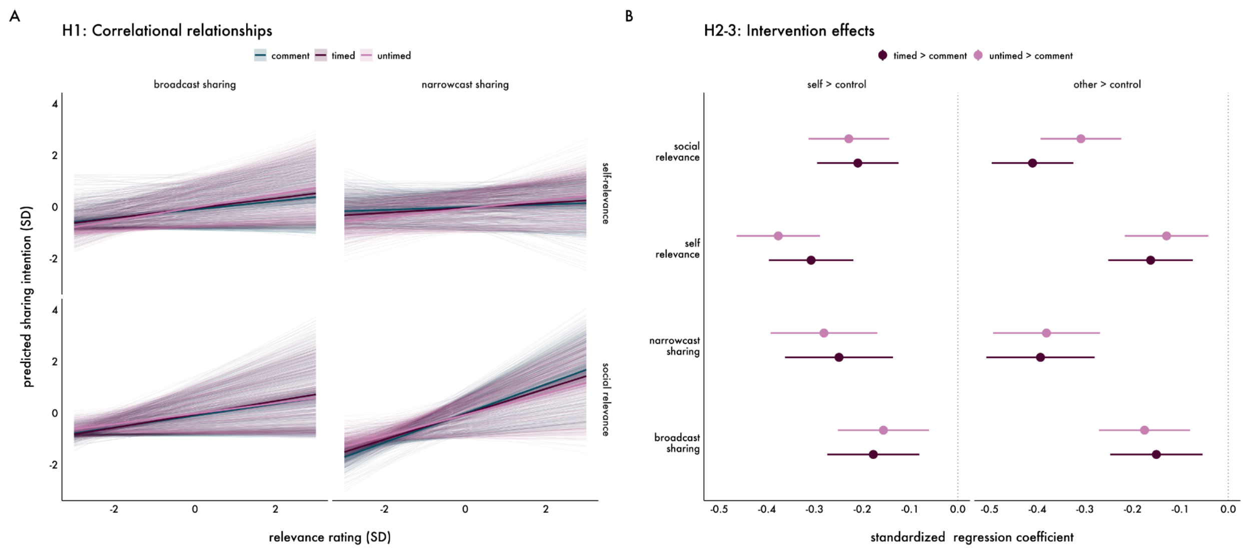

Figure S4. (A) Correlational relationships between self and social relevance (x-axis) and predicted broad- and narrowcast sharing intentions (y-axis) as a function of group. Model predicted values are overlaid on individual predicted slopes. Error bands are 95% confidence intervals. (B) Group differences in causal effects (x-axis) of the content-framing interventions on self-relevance, social relevance, broad- and narrowcast sharing intentions (y-axis) for the self-focused intervention (left panel) and the other-focused intervention (right panel) versus the control condition. Relative to the comment group, both the timed and untimed reflection groups were less effective resulting in lower perceptions of self and social relevance, as well as broad- and narrowcast sharing intentions. The dotted line represents the average effect in the comment group and error bars are 95% confidence intervals.

Table S16

Results from Study 4 models testing hypotheses H1-3

Dependent variable	Term	*β [95% CI]*	*df*	*t*	*p*
H1a-b: Broadcast sharing intention	intercept	-0.11 [-0.23, 0.01]	458.36	1.88	.061
	self-relevance	0.16 [0.10, 0.22]	331.72	5.29	< .001
	group (timed)	0.05 [-0.11, 0.21]	442.85	0.64	.525
	group (untimed)	0.08 [-0.07, 0.23]	443.26	1.02	.308
	social relevance	0.23 [0.17, 0.29]	347.90	7.17	< .001
	self-relevance x group (timed)	0.03 [-0.05, 0.11]	338.44	0.73	.463
	self-relevance x group (untimed)	0.09 [0.01, 0.17]	334.40	2.32	.021

	social relevance x group (timed)	0.03 [-0.05, 0.11]	347.04	0.70	.487
	social relevance x group (untimed)	-0.03 [-0.11, 0.06]	345.11	0.62	.537
H1a-b: Narrowcast sharing intention	intercept	-0.02 [-0.12, 0.08]	451.88	-0.46	.649
	self-relevance	0.05 [-0.01, 0.12]	282.28	1.59	.113
	group (timed)	-0.03 [-0.16, 0.10]	434.90	0.42	.675
	group (untimed)	-0.05 [-0.18, 0.07]	436.13	0.85	.398
	social relevance	0.56 [0.49, 0.64]	360.20	15.16	< .001
	self-relevance x group (timed)	0.04 [-0.04, 0.13]	290.35	0.97	.332
	self-relevance x group (untimed)	0.11 [0.02, 0.20]	285.87	2.53	.012
	social relevance x group (timed)	-0.07 [-0.17, 0.03]	364.22	1.46	.145
	social relevance x group (untimed)	-0.15 [-0.25, -0.05]	359.77	3.07	.002
H2a: Self-relevance	control	0.01 [-0.12, 0.14]	607.40	0.20	.844
	other - control	0.12 [0.05, 0.18]	10109.18	3.43	< .001
	self - control	0.44 [0.37, 0.51]	10108.40	12.85	< .001
	group (timed)	-0.10 [-0.25, 0.05]	562.50	1.26	.208
	group (untimed)	-0.12 [-0.27, 0.03]	563.72	1.52	.130
	other - control x group (timed)	-0.16 [-0.25, -0.07]	10105.42	3.60	< .001
	self - control x group (timed)	-0.31 [-0.40, -0.22]	10102.49	6.82	< .001
	other - control x group (untimed)	-0.13 [-0.22, -0.04]	10106.53	2.89	.004
	self - control x group (untimed)	-0.38 [-0.46, -0.29]	10108.99	8.43	< .001
H2b: Social relevance	control	-0.01 [-0.15, 0.12]	621.63	0.21	.830
	other - control	0.42 [0.36, 0.49]	10111.86	12.78	< .001
	self - control	0.30 [0.23, 0.36]	10111.82	9.00	< .001
	group (timed)	-0.10 [-0.26, 0.06]	539.49	1.18	.237
	group (untimed)	-0.13 [-0.29, 0.03]	540.45	1.62	.106
	other - control x group (timed)	-0.41 [-0.50, -0.32]	10109.14	9.40	< .001
	self - control x group (timed)	-0.21 [-0.30, -0.12]	10106.04	4.81	< .001
	other - control x group (untimed)	-0.31 [-0.39, -0.22]	10110.70	7.15	< .001
	self - control x group (untimed)	-0.23 [-0.31, -0.14]	10113.01	5.30	< .001
H3: Broadcast sharing intention	control	-0.09 [-0.25, 0.06]	545.83	1.17	.244
	other - control	0.21 [0.13, 0.28]	4812.68	5.55	< .001
	self - control	0.18 [0.11, 0.26]	4814.83	4.90	< .001
	group (timed)	0.06 [-0.15, 0.26]	520.52	0.54	.591
	group (untimed)	0.06 [-0.14, 0.26]	521.24	0.59	.556
	other - control x group (timed)	-0.15 [-0.25, -0.05]	4812.93	3.06	.002
	self - control x group (timed)	-0.18 [-0.27, -0.08]	4809.25	3.60	< .001
	other - control x group (untimed)	-0.18 [-0.27, -0.08]	4815.83	3.60	< .001
	self - control x group (untimed)	-0.16 [-0.25, -0.06]	4817.33	3.21	.001
H3: Narrowcast sharing intention	control	-0.08 [-0.22, 0.07]	624.88	1.05	.292
	other - control	0.42 [0.33, 0.51]	4809.39	9.60	< .001
	self - control	0.28 [0.19, 0.36]	4810.82	6.34	< .001
	group (timed)	0.02 [-0.17, 0.21]	575.78	0.18	.858
	group (untimed)	-0.01 [-0.19, 0.18]	577.00	0.08	.937
	other - control x group (timed)	-0.39 [-0.51, -0.28]	4808.50	6.81	< .001
	self - control x group (timed)	-0.25 [-0.36, -0.14]	4804.93	4.32	< .001
	other - control x group (untimed)	-0.38 [-0.49, -0.27]	4811.05	6.66	< .001

self - control x group (untimed)	-0.28 [-0.39, -0.17]	4812.81	4.92	< .001

Within the comment group, engaging more deeply with the prompts by writing longer comments was associated with higher perception of self and social relevance, as well as sharing intentions. We also replicate these relationships with comment word count in Studies 1-2 (Table S4). This suggests that deeper engagement (e.g., through writing) is necessary for the content-framing interventions to work.

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