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Message Self and Social Relevance Increases Intentions to Share Content: Correlational and Causal Evidence From Six Studies

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Information sharing within social networks can catalyze widespread attitudinal and behavioral change and the chance to share information with others has been characterized as inherently valuable to people. But what are the sources of value and how might they be leveraged to promote sharing? We test ideas from the value-based virality model that the value of sharing increases when people perceive messages as more relevant to themselves and to people they know, resulting in stronger intentions to share. We extend this work by considering how sharing context—broadcasting to a wide audience or narrowcasting directly to someone—may alter these relationships. Six online studies with adults in the United States (*N* participants = 3,727; messages = 362; message ratings = 30,954) showed robust evidence that self and social relevance are positively and uniquely related to sharing intentions within- and between-person. Specification curve analysis showed these relationships were consistent across message content (COVID-19, voting, general health, climate change), medium (social media post and news articles), and sharing context (broad- and narrowcasting). A preregistered experiment showed that manipulating the self and social relevance of messages through a framing manipulation causally increased sharing intentions. These causal effects were mediated by changes in both self and social relevance, but the relative strength of the causal pathways differed depending on sharing context. These findings extend existing

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Data, code, and preregistration links: https://osf.io/bgs5y; https://github.com/cnlab/self-social-sharing.

In acknowledgment 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 article was drafted, six authors self-identified as women and four authors as men. With respect to race and ethnicity, one author self-identified as Chinese, one author as South Asian, seven authors as White, and one author as White Hispanic. With respect to age, all authors are 40 years old or younger.

Recent work in several fields of science has identified a bias in citation practices such that articles from women and other minority scholars are under-cited relative to the number of such articles 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., n.d.). 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 (and excluding self-citations to Danielle Cosme and Emily B. Falk of our current article), our references contain 21% woman(first)/woman(last), 13% man/woman, 30% woman/man, and 36% man/man. 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, nonbinary, or transgender people.

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models of information sharing, and highlight self and social relevance as psychological mechanisms that motivate information sharing that can be targeted to promote sharing across contexts.

Keywords: sharing, social media, self-relevance, norms, virality

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At this moment, we are facing various global crises—from the COVID-19 pandemic, to climate change—that require large-scale attitudinal and behavioral change. For widespread action, it is vital that accurate and persuasive information is transmitted between people. When people share information with one another, it also affects what people perceive as normative (Tankard & Paluck, 2016) and hence how they behave (Cialdini et al., 1991; Jeong & Bae, 2018). Sharing information is a fundamental aspect of human social interaction that catalyzes social change (Barberá et al., 2015) and has been characterized as inherently valuable to people (Tamir & Mitchell, 2012; Vijayakumar et al., 2020). In the current study, we examine potential sources of this value and how they can be leveraged to promote information sharing. Bringing together insights from psychology, neuroscience, communication, and marketing, we test the hypotheses that when people see information as being relevant to themselves and to people in their social networks, these sources of value motivate them to share with others. Further, we add nuance to prior theorizing by examining how the sharing context affects the psychological processes that are most important in deciding what to share.

Sharing as a Value-Based Decision

The value-based virality model asserts that decisions to share information are a particular case of value-based decision making which involves selecting choice options based on their relative value (Falk & Scholz, 2018; Scholz et al., 2017). The perceived costs and benefits of each option are implicitly and explicitly weighed and integrated into a common currency—subjective value—that enables comparison between options (Levy & Glimcher, 2012). Neuroscientific research demonstrates that decisions to share information (Baek et al., 2017; Scholz, Jovanova, et al., 2020) and population-level outcomes such as popularity, campaign effectiveness, and message virality (Doré et al., 2019; Falk et al., 2012; Genevsky & Knutson, 2015), are associated with increased activity in the brain's valuation system. But what factors might be integrated during subjective value calculation when deciding whether or not to share information?

Research on persuasion and communication highlights characteristics of the information and of the individual sharer as important features (Cappella et al., 2015; Kümpel et al., 2015). For example, how positive (Al-Rawi, 2019), emotionally arousing (Berger & Milkman, 2012), controversial (Kim, 2021), or useful (Kim, 2015) content is perceived to be, is positively associated with sharing and virality. An individual's implicit motives, such as social bonding (Baek et al., 2019) and impression management (Ihm & Kim, 2018), and explicit goals, such as information seeking (Lee & Ma, 2012) and persuasion (Berger, 2014), also shape sharing behavior. Applying the value-based decision framework to these findings suggests a parsimonious mechanism (i.e., valuation) through which a sharer can account for, compare, and integrate these disparate factors when deciding to share.

From a translational perspective, any of these factors might be used as levers to increase or decrease the subjective value associated with the decision to share. However, these diverse inputs can be broadly characterized as self-related or social concerns, which in turn can be captured by self and social relevance—the perceived relevance to other people within the person's social network. For example, self-relevance encompasses various self-related processes and motivations, such as emotional experience, goals, self-expression, self-enhancement. This article focuses on these two sources of value because they are central in psychological theories of persuasion and social influence (for a review, see Falk & Scholz, 2018) and represent practical targets for sharer-focused interventions to promote sharing behavior. Such interventions could frame information in different ways to enhance its perceived self or social relevance, thereby increasing subjective value and the likelihood of sharing, without altering the content itself (which may distract or distort the information). Because this approach relies on framing alone and could operate through any number of idiosyncratic factors an individual views as self or socially relevant (e.g., the content is viewed as useful, in line with one's goals, or affords the opportunity to connect), it may alter subjective value in a relatively scalable way.

Self and Social Relevance

Information related to the self is expected to have higher subjective value for several reasons. First, there are well-documented egocentric biases in which individuals tend to pay greater attention to (Humphreys & Sui, 2016), process information more efficiently (Markus, 1977; Meyer & Lieberman, 2018), and overvalue objects and attributes perceived as being related to the self (Beer & Hughes, 2010; Kahneman et al., 1991; Mezulis et al., 2004; Taylor & Brown, 1988). Second, there is substantial overlap between brain regions supporting self-referential processing and valuation (Berkman et al., 2017; Chavez et al., 2017; D'Argembeau, 2013; Pfeifer & Berkman, 2018), suggesting that these processes are intimately intertwined. Finally, disclosing information about oneself is thought to be intrinsically rewarding and therefore subjectively valued (Tamir & Mitchell, 2012).

Social relevance is also hypothesized to increase subjective value in the context of sharing decisions. Humans have a fundamental need to belong (Baumeister & Leary, 1995) and can connect by sharing information. Sharing feels good and is associated with activity in the brain's reward and valuation systems (Tamir et al., 2015). When communicating, individuals consider what is relevant to their audience in order to tailor their communication effectively (Berger, 2014; Echterhoff et al., 2009) and this ability is supported by the tendency to spontaneously consider and predict others' mental states (Koster-Hale & Saxe, 2013; Mildner &

Tamir, 2021; Thornton et al., 2019). In addition, individuals are motivated to conform to social norms and are therefore likely to consider what people will think of them if they share (Schultz et al., 2007).

Integrating this evidence with the observations from neuroscientific research on value-based decision making, the value-based virality model (Scholz et al., 2017) proposes that information that is perceived as more self and/or socially relevant will have higher subjective value during valuation, and therefore be more likely to be shared and go viral. There is indirect evidence from neuroimaging studies supporting this hypothesis; brain regions associated with self-referential processing and social cognition are related to sharing intentions (Baek et al., 2017; Scholz, Baek, et al., 2020) and population-level virality (Scholz et al., 2017). However, it is unclear whether: (a) explicit evaluations of self and social relevance—which are less costly to measure—are similarly related to sharing behavior, (b) self and social relevance can be causally manipulated to promote information sharing, and (c) these relationships generalize across contexts, such as the type of content being shared and the audience being targeted.

Broad- Versus Narrowcast Sharing

While much of the existing psychological work on sharing has treated it as a single, homogeneous behavior, some prior work in communication and marketing has highlighted the need for nuance, distinguishing different forms of sharing based on the audience size (Barasch & Berger, 2014). "Broadcasting" is sharing information with a large and often ill-defined group of individuals (e.g., via public posts on social media), whereas "narrowcasting" is sharing information with one or a small group of well-defined individuals (e.g., via a direct message). Audience size is an important contextual variable for sharing research, because it has implications for the reach and impact of the shared piece of information, as well as for the impact sharing may have on the information sharer (Scholz, Baek, et al., 2020). For instance, narrowcasting leads to fewer additional exposures to the shared content than broadcasting, but since the shared information is specifically targeting one or few individuals, narrowcasting may be more likely to elicit prolonged attention and responses. Further, broadcasters compared to narrowcasters generally deal with greater potential diversity and uncertainty regarding the opinions and existing knowledge of their audiences, which may have implications for the sharing of controversial content or the way in which content is shared. In fact, research has shown that information sharers engage in so-called audience tuning, meaning that they adjust what they share and how they do so, depending on audience characteristics (Echterhoff et al., 2009), and the most tuning will occur when tailoring messages to a specific person when narrowcasting. Pronounced differences in the social and content-related implications of narrow- and broadcasting bring with them related differences in the psychological motivations and experiences of broad- and narrowcasters.

Importantly, self-related and social motivations have been hypothesized to play differential roles in broad- versus narrowcasting. For instance, some have argued that self-related motivations, such as self-presentation, self-enhancement, and self-expression (Berger, 2014), play a larger role in broadcasting because uncertainty about the precise make-up of the audience in terms of individual members, options, and so forth leads sharers to focus more on themselves rather than specific audience characteristics. On the other hand, social motivations, such as connecting with or helping others (Berger, 2014), may be more important in narrowcasting because the audience is well-defined and messages are more easily tailored to meet the target's needs. Although initial research testing these hypotheses pitted self and other motivations against one another (Barasch & Berger, 2014), neuroimaging research suggests that self and social processing are involved in both broad- and narrowcasting and that differences between sharing types are related to the relative degree of engagement (Scholz, Baek, et al., 2020). We extend prior work by integrating these findings with the value-based virality model, which did not originally consider contextual factors, such as audience size. Specifically, we test the hypothesis that contextual factors such as audience size change the relative importance of different decision attributes in terms of their impact on the overall computation of the value of sharing. That is, we expect that the relative contribution of self and social relevance to the calculation of subjective value varies based on the sharing audience—self-relevance would be expected to weigh more heavily during decisions to broadcast, and social relevance would be expected to weigh more heavily during decisions to narrowcast.

The Present Research

Across six online studies (participant N = 3,727; Table 1), we tested correlational relationships between the self and social relevance of informational messages and intentions to share them (Studies 1–6), and whether experimentally manipulating self and social relevance causally increases message sharing intentions (Study 6). We focused on messages about important societal issues (messages n = 362; message ratings n = 30,954), and assessed the generalizability of these relationships across message content

Table 1
Overview of Studies

Study	N	Content	Medium	Sharing type	Type
Study 1	2,081	COVID-19	Social media	Broadcast	Correlational
Study 2	547	Voting	Social media	Broadcast	Correlational
Study 3	248	Voting	Social media	Broad- & narrowcast	Correlational
Study 4	139	Health	Newspapers	Broadcast	Correlational
Study 5[a]	315	COVID-19 & climate change	Newspapers	Broad- & narrowcast	Correlational
Study 6[a]	397	Health & climate change	Newspapers	Broad- & narrowcast	Correlational & causal

Note. Study 1 combines data from four samples from the same project.
[a] Preregistered study.

(COVID-19, voting, general health, climate change) and medium (social media posts, newspaper articles). Given that self and social relevance may differentially contribute to decisions to share depending on the audience (Scholz, Baek, et al., 2020), we also examined how these relationships may differ as a function of sharing context (broadcast and narrowcast sharing). Because it is unclear whether the relationships between self and social relevance and sharing are driven by message-induced responses or by individual differences in the propensity to view content as self and/or socially relevant, we distinguished within- and between-person relationships using multilevel modeling. We also examined the robustness of these relationships across alternative model specifications and within specific subsets of the data using specification curve analysis.

Open Practices Statement

Studies 1–4 used existing data, whereas Studies 5 and 6 were preregistered before collecting data (https://osf.io/bgs5y/registrations). The sample sizes for Studies 5 and 6 were based on power calculations described in the preregistrations. Standard operating procedures for Studies 5 and 6 are available online (https://osf.io/bgs5y/). The data and analysis code needed to reproduce the main analyses reported here are available online (https://github.com/cnlab/self-social-sharing). Individual demographic data is not posted publicly due to concerns related to potential identifiability of participants, but is available upon request. The messages used in this study are available online (https://osf.io/nfr7h/). In response to reviewer feedback noting the strong relationship between self and social relevance, we deviated from our preregistration by estimating mediation models that included self and social relevance as parallel mediators (vs. only including one mediator as preregistered) to assess the specificity of the experimental effects on sharing intentions. For transparency, we also include the original, preregistered models in online supplementary material.

Correlational Analyses

Method

Participants

These analyses included data from six online studies (N = 3,727) using convenience sampling. Participants were living in the United States and aged 18 to 81 (M = 38.1, SD = 12.0). With respect to gender, participants identified as the following: 52.5% men, 46.6% women, 0.2% nonbinary or third gender, 0.2% identified as another category ("other"), and 0.4% preferred not to say. With respect to race and ethnicity (not reported in Study 4), participants identified as the following: 76.9% White, 11.5% Hispanic or Latina/Latino/Latinx, 10.6% Black or African American, 8.6% Asian, 0.9% More than one race, 0.8% American Indian or Alaskan Native, 0.1% Native Hawaiian or Other Pacific Islander, 1.5% as another race ("other"), and 0.6% preferred not to say. Additional demographic information, demographic information by study, and the specific inclusion and exclusion criteria for each study is reported in the online supplementary material. Study 4 was conducted online through the Human Subjects Pool at the University of Pennsylvania; all other studies were conducted online through Amazon's Mechanical Turk (MTurk). All studies were approved by the University of Pennsylvania Institutional Review Board or deemed exempt from review, and all participants gave informed consent and were compensated financially or with course credit.

Procedure

Participants were exposed to 5–10 messages about COVID-19, voting, general health, or climate change (see Table 1). In Studies 1–3, these messages were framed as social media posts, whereas in Studies 4–6 they were headlines and brief abstracts from *New York Times* newspaper articles. After reading each message, participants rated self-relevance (e.g., "This message is relevant to me") and social relevance (e.g., "This message is relevant to people I know"). Two types of sharing intentions were measured: broadcast and narrowcast. In all studies, participants rated their broadcast intention to share on social media (e.g., "I would share this article by posting on social media [on Facebook, Twitter, etc.]"). In Studies 3, 5, and 6 they also rated their narrowcast intention to share directly with someone (e.g., "I would share this article directly with someone I know [via email, direct message, etc.]"). The specific language and scales differed across studies; see the online supplementary material for study-specific details. Responses were z-scored within study in order to conduct analyses across studies.

Statistical Analyses

We investigated the relationships between message self and social relevance and sharing intentions using multilevel modeling. We included self and social relevance in the same models to examine their unique relationships with sharing intentions (see online supplementary material for separate models). Self and social relevance ratings were disaggregated into within and between-person variables. The within-person self and social relevance variables were Level 1 predictors, centered within-person (i.e., "centered within context") and standardized across people within each study. These variables represent message-level deviations from a person's average self or social relevance rating. Each of the between-person variables were Level 2 predictors created by averaging across the self or social relevance ratings of all messages to create a single average per person that was then grand-mean centered and standardized across people within each study. These variables represent person-level deviations from the average self or social relevance rating across people. All models were estimated using the *lme4* (Version 1.1–26; Bates et al., 2015) and *lmerTest* (Version 3.1–3; Kuznetsova et al., 2017) for significance testing in R (Version 3.6.3; R Core Team, 2020). Degrees of freedom (*df*) were calculated using the Satterthwaite approximation. All p-values reported are from two-tailed tests. The specification curve analysis was implemented using code adapted from *specr* (Masur & Scharkow, 2020). All software packages used are listed in the online supplementary material.

Mega-Analysis. We used a mega-analysis approach (Eisenhauer, 2021) to pool raw data from all six studies and precisely estimate the correlational relationships between self and social relevance, and sharing intentions, as a function of sharing type (broad- or narrowcasting). We estimated a single multilevel model with the within- and between-person self and social relevance variables, and their interactions with sharing type as predictors. We adopted the least constrained random effects structure that converged; intercepts and within-person self and social relevance were allowed to vary randomly across people and messages. Although the variance inflation factors (VIF) for the predictor variables were small to moderate (VIF range = 1.00–4.24), we conducted a sensitivity analysis to assess the impact of multicollinearity on the estimated regression coefficients. Specifically, we estimated the mega-analysis model in a subset of the data where message-level correlations (i.e., the correlation between self and social relevance for a given message) below $r = .70$. These analyses are presented in the online supplementary material; the results did not change appreciably from those reported in the main article. For completeness, we also present analyses for each study individually as well as the mega-analysis estimated for self and social relevance separately (i.e., not in the same model) in online supplementary material.

Specification Curve Analysis. We used specification curve analysis (SCA) to explore the robustness of the relationships between self and social relevance, and sharing intentions. Briefly, SCA can be used to map a collection of possible models that could be specified to test a given hypothesis (Simonsohn et al., 2020; Steegen et al., 2016). Because the studies in this article varied with respect to content, medium, and sharing type, we used SCA to estimate the relationships between message self and social relevance, and sharing intentions within specific subsets of the data, as well as when adjusting for demographic covariates. Specifically, we included within- and between-person self and social relevance as predictors of interest and included each of the following demographic covariates: age, gender, race, ethnicity, highest degree completed, and household income. This resulted in a set of seven possible model specifications for each relevance variable, including models with no demographic covariates. We then created 13 unique subsets of the data based on message content, medium, and sharing type (e.g., broadcasting across social media messages or narrowcasting across newspaper articles about COVID-19; see online supplementary material for a full list of subsets), and estimated the set of model specifications for each relevance variable within each subset. Not all studies included the same demographic variables and therefore studies missing specific demographic covariates are not included in the estimation of the corresponding model specifications. Together, this resulted in 86 per relevance variable (a total of 344 model specifications). For each model specification, we extracted the standardized regression coefficient for the predictor of interest, ordered them by effect size, and plotted them to form a specification curve for each relevance variable separately. For each model specification in the curve, we visualized which relevance variable was the predictor of interest, the content type, medium, sharing type, and whether or not demographic covariates were included. In line with recent recommendations to avoid inflating the model space with poorly specified models (Del Giudice & Gangestad, 2021), we conceptualize this set of analytic decisions as uncertain ("Type-U") because the decision options are not clearly equivalent or nonequivalent, and treat these analyses as exploratory, focusing on descriptive rather than inferential statistics.

Results

Descriptives

Table 2 shows the means, standard deviations, and correlations between the self and social-relevance survey ratings and sharing variables for each study separately. Within-person correlations were estimated using the *rmcorr* package (Bakdash & Marusich, 2017).

Mega-Analysis

With pooled data from all six studies, we estimated a single multilevel model to assess the relationship between within-person and between-person self and social relevance and intentions to share, and whether these relationships differ as a function of

Table 2

Means, Standard Deviations, and Repeated Measures Correlations for Each Study

				r [95% CI]		
Study	Variable	Range	*M (SD)*	Self-relevance	Social relevance	Broadcast
Study 1	Self	1–7	5.4 (1.5)	—	—	—
	Social	1–7	5.7 (1.4)	0.66 [0.65, 0.67]	—	—
	Broadcast	1–7	4.5 (2.0)	0.45 [0.43, 0.47]	0.45 [0.43, 0.46]	—
Study 2	Self	0–100	63.0 (30.7)			
	Social	0–100	69.2 (26.3)	0.60 [0.58, 0.63]		
	Broadcast	0–100	49.2 (35.9)	0.31 [0.27, 0.34]	0.31 [0.27, 0.35]	
Study 3	Self	0–100	69.4 (27.1)	—	—	—
	Social	0–100	76.7 (21.7)	0.69 [0.65, 0.72]	—	—
	Broadcast	0–100	43.6 (33.3)	0.36 [0.30, 0.41]	0.35 [0.29, 0.40]	—
	Narrowcast	0–100	48.4 (33.5)	0.40 [0.35, 0.45]	0.34 [0.37, 0.48]	0.68 [0.64, 0.71]
Study 4	Self	0–10	4.1 (3.4)	—	—	—
	Social	0–10	5.8 (2.7)	0.59 [0.55, 0.63]	—	—
	Broadcast	0–10	3.8 (3.4)	0.64 [0.61, 0.68]	0.55 [0.50, 0.59]	—
Study 5	Self	0–100	56.8 (29.8)	—	—	—
	Social	0–100	61.5 (27.9)	0.71 [0.70, 0.73]	—	—
	Broadcast	0–100	49.8 (32.3)	0.52 [0.50, 0.55]	0.46 [0.43, 0.49]	—
	Narrowcast	0–100	50.3 (32.1)	0.48 [0.45, 0.51]	0.53 [0.50, 0.55]	0.67 [0.65, 0.69]
Study 6	Self	0–100	57.3 (32.2)	—	—	—
	Social	0–100	62.8 (29.6)	0.67 [0.65, 0.69]	—	—
	Broadcast	0–100	47.2 (34.6)	0.49 [0.46, 0.51]	0.47 [0.44, 0.49]	—
	Narrowcast	0–100	48.8 (33.5)	0.48 [0.45, 0.50]	0.57 [0.55, 0.60]	0.59 [0.57, 0.61]

Note. Range = scale range; broadcast = broadcast sharing intentions; narrowcast = narrowcast sharing intentions; self = self-relevance; social = social relevance.

sharing type. Because the self and social relevance variables were included in the same model, the parameter estimates reflect their unique effects after adjusting for the other variables in the model. First, we report the main effects of these variables on broadcasting, which was the reference group for sharing type. Then, we report the interactions that test whether these relationships differed between broad- and narrowcast sharing intentions. Between-person relationships reflect average deviations from the group mean, whereas within-person relationships reflect deviations from a persons' mean.

Broadcasting. Integrating across studies revealed a moderate positive relationship with between-person self-relevance (β = 0.35, 95% CI [0.31, 0.39]) and a small positive relationship with between-person social relevance (β = 0.16, 95% CI [0.12, 0.20]). This indicates that people who tended to perceive messages as more self and socially relevant also tended to report higher sharing intentions. Within-person there were small positive relationships with self-relevance (β = 0.18, 95% CI [0.17, 0.20]) and social relevance (β = 0.13, 95% CI [0.12, 0.14]), indicating that when people perceived messages as more self and socially relevant (compared to their own average perceived relevance), they also reported higher intentions to share it.

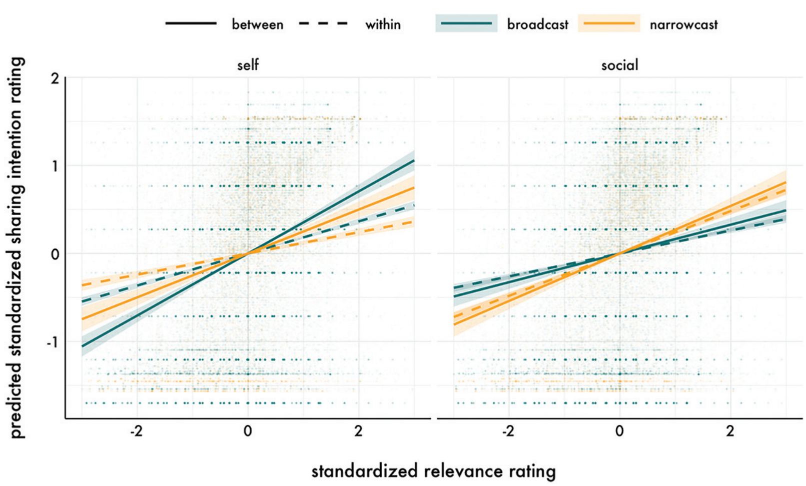
Broadcasting Versus Narrowcasting. Next we tested the interaction between each relevance variable and sharing type. Between people, the relationship between self-relevance and sharing intentions was weaker when narrowcasting compared to broadcasting ($\beta_{interaction}$ = −0.10, 95% CI [−0.13, −0.07]), whereas the relationship between social relevance and sharing intentions was stronger when narrowcasting ($\beta_{interaction}$ = 0.11, 95% CI [0.08, 0.14]). This indicates that people who tend to rate messages as more relevant to themselves also tend to have higher sharing intentions when broadcasting compared to narrowcasting, whereas people who rate messages as more socially relevant have stronger sharing intentions when narrowcasting compared to broadcasting. The same pattern was observed for within-person self-relevance ($\beta_{interaction}$ = −0.06, 95% CI [−0.08, −0.04]) and social relevance ($\beta_{interaction}$ = 0.11, 95% CI [0.09, 0.13]). When people rated messages as more relevant to themselves, they had higher intentions to share them when broadcasting compared to narrowcasting, and when people rated messages as more socially relevant, they had higher intentions to share them when narrowcasting compared broadcasting. These relationships are visualized in Figure 1 and model parameters and statistics are presented in Table 3.

Specification Curve Analysis

Overall, the relationships between self and social relevance, and sharing intentions, generalized across message content type, content medium, and sharing type, and were robust to the inclusion of demographic covariates. Between-person self-relevance was consistently the strongest predictor of sharing intentions after adjusting for the other relevance variables in the model (Figure 2; Table 4). Across all model specifications, between-person self-relevance (Median β = 0.46, range = 0.22–0.74), and within-person self (Median β = 0.16, range = 0.08–0.22) and social relevance (Median β = 0.14, range = 0.10–0.30) were positively related to sharing

Figure 1

The Predicted Within- and Between-Person Relationships for Relevance Ratings and Sharing Intention Ratings From the Mega-Analysis as a Function of Within- and Between-Person Relevance Variable (Self or Social) and Sharing Type (Broad- or Narrowcasting)



Note. The points represent the raw (i.e., not predicted) message-level responses; error bands are 95% confidence intervals. This plot shows that all variables are positively related to sharing intentions. The left panel visualizes the relationships between sharing intentions and self-relevance, and shows that the relationship with sharing intentions is stronger when broadcasting compared to narrowcasting for both within- and between-person self-relevance. The right panel visualizes the relationships between sharing intentions and social relevance, and shows that the relationship with sharing intentions is stronger when narrowcasting compared to broadcasting for within- and between-person social relevance. See the online article for the color version of this figure.

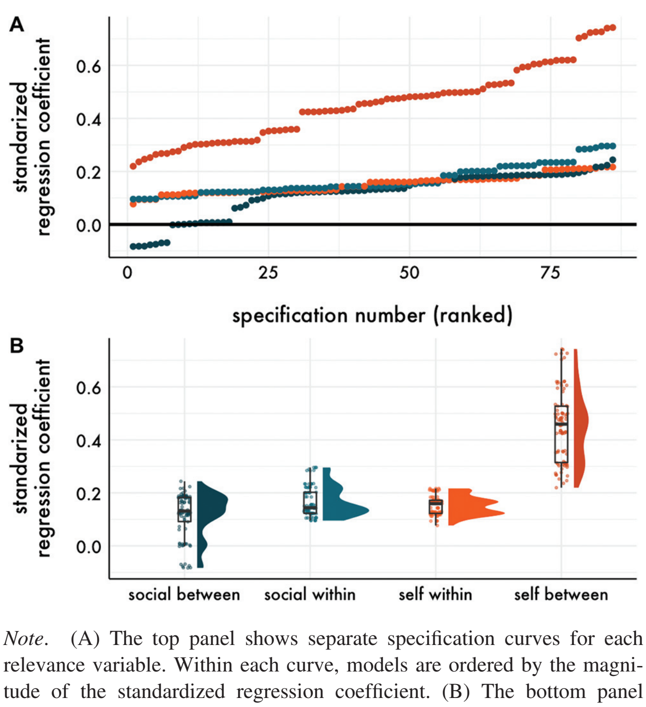
Table 3
Results From the Mega-Analysis Model of Predictors of Sharing Intentions

Parameter	β [95% CI]	*d*	*df*	*t*	*p*
Sharing type	−0.00 [−0.01, 0.01]	0.00	23,772.62	0.01	.990
Self between	0.35 [0.31, 0.39]	0.58	3,776.06	17.94	<.001
Self within	0.18 [0.17, 0.20]	2.46	325.24	22.16	<.001
Social between	0.16 [0.12, 0.20]	0.27	3,743.23	8.33	<.001
Social within	0.13 [0.12, 0.14]	2.06	287.62	17.49	<.001
Self Between × Sharing Type	−0.10 [−0.13, −0.07]	0.09	23,690.57	7.08	<.001
Self Within × Sharing Type	−0.06 [−0.08, −0.04]	0.11	13,738.55	6.57	<.001
Social Between × Sharing Type	0.11 [0.08, 0.14]	0.09	23,694.57	7.30	<.001
Social Within × Sharing Type	0.11 [0.09, 0.13]	0.22	11,895.65	11.57	<.001

Note. "Within" parameters refer to the person-centered Level 1 predictors, whereas "between" parameters refer to grand-mean centered Level 2 predictors. The reference group for sharing type is broadcast sharing intentions. Coefficients are in standardized units. Degrees of freedom (*df*) were calculated using the Satterthwaite approximation.

intentions and these relationships were statistically significant in every model. This means that people who tended to rate the messages as more relevant to themselves were also more likely to intend to share the messages, and when people rated messages as more relevant to themselves and to others they also reported higher intentions to share them. The relationship between sharing intentions and between-person social relevance was less consistent. Most models were positively related to sharing intentions (Median β = 0.13, range = −0.08–0.24), but these relationships were only statistically significant in 63.95% of the models. Inspection of the model subsets (Table S3, Figures S3–4 in the online supplemental material) showed that this was due to negative coefficients from models of broadcasting newspaper articles about COVID-19 (Study 5) and nonsignificant coefficients from models of broadcasting newspaper articles about climate change (Studies 5 and 6). Because Studies 5 and 6 also had the highest average correlations between message-level self and social relevance (Table S1 in the online supplemental material, mean *r*s = .73–.84), it seems likely that the coefficients from these models were less stable due to multicollinearity (see online supplementary material for separate models).

Figure 2
Specification Curve Comparison



Note. (A) The top panel shows separate specification curves for each relevance variable. Within each curve, models are ordered by the magnitude of the standardized regression coefficient. (B) The bottom panel shows the distribution of standardized regression coefficients in the curve and box and whisker plots depicting the curve median (the horizontal line), the interquartile range (the box), and +/−1.5 times the interquartile range from the box hinge (the vertical lines), for each relevance variable separately. See the online article for the color version of this figure.

The specification curves also revealed two interesting dissociations between self and social relevance. First, the relationship between sharing intentions and between-person self-relevance was consistently stronger for newspaper articles compared to social media messages (collapsed across content type), whereas between-person social relevance tended to be more strongly associated with sharing intentions for social media messages (Figure 3A–B; Table S3 in the online supplemental material). Second, within-person self-relevance tended to be more strongly associated with broadcast sharing intentions than narrowcast sharing intentions, whereas the opposite was true for within-person social relevance (Figure 3C–D; Table S3).

Causal Experiment Analyses

We extend the correlational findings by testing whether self and social relevance are causally related to sharing intentions in a preregistered experiment. Self and social relevance were experimentally manipulated by having participants explicitly reflect on the self or social relevance of messages.

Method

Participants

This preregistered study was conducted online through MTurk. Participants were included if they were adults 18 or older, residing in the United States, were fluent in English, and passed an initial attention screening question. Participants were excluded based on the standard operating procedures for this project. Of the 644 participants initially recruited, participants were excluded for failing the English comprehension question (n = 20), one or more attention check (n = 80), or for not providing comprehensible text during the experimental manipulation (n = 233), which was

Table 4
Specification Curve Descriptives Statistics

Parameter	Median β	β range	Positive and significant	Negative and significant
Self between	0.46	0.22, 0.74	100%	0%
Self within	0.16	0.08, 0.22	100%	0%
Social between	0.13	−0.08, 0.24	64%	0%
Social within	0.14	0.10, 0.30	100%	0%

Note. This information is further broken down by sharing type and message medium in Table S3.

evaluated by two researchers before any hypothesis testing, consistent with our preregistered plan. This yielded a final sample of 397.

Procedure

Participants were randomly assigned to either the self (n = 200) or social (n = 197) condition. We used a mixed design in which all participants saw a set of five messages in the control condition and a set of five messages either in the self condition or the social condition. Therefore, relationships between the experimental condition (self or social) and the control condition were assessed within-person, whereas the difference between experimental conditions was assessed between-person. We manipulated self relevance by asking participants to write about *why the article matters to them personally* (self condition), and social relevance by asking them to write about *why the article matters to people they know* (social condition). In the control condition, participants did not reflect on relevance and instead were asked to write *what the article is about*. Messages consisted of a news headline and brief abstract from the *New York Times* about general health or climate change—two important societal issues that could benefit from individual and collective action. Participants rated self and social relevance, and broad- and narrowcast sharing intentions in a similar manner as the Studies 1–5 (see online supplementary material). For further methodological details, including the full instructions for the task, see online supplementary material.

Statistical Analyses

First, we conducted two manipulation checks to confirm that the experimental manipulations increased self and social relevance compared to the control condition. In separate multilevel models, we regressed self or social relevance ratings on the experimental condition (self, social, or control), and the control condition was specified as the reference. The intercept and condition slope were allowed to vary randomly across participants. Next, we tested the hypothesis that the experimental manipulations would increase message sharing intentions relative to the control condition using multilevel modeling, and also tested whether the relationship between condition and sharing intention was moderated by sharing audience (broad- or narrowcast). We regressed sharing intentions on condition, sharing type, and their interaction, and allowed the intercept and sharing audience to vary randomly across participants (which was the least constrained model that converged). Standard effect sizes were computed using the *lme.dscore* function from the *EMAtools* packages (Version .1.4; Kleiman, 2021). Finally, we fit four within-person Bayesian mediation models testing the degree to which the effect of the experimental condition (self vs. control, or social vs. control) on sharing intentions was mediated by self and social relevance, separately for broadcasting and narrowcasting. Self and social relevance were included as parallel mediators (see online supplementary material for separate models). Intercepts and experimental condition were allowed to vary randomly across people. The raw units were retained here (vs. standardizing) to facilitate interpretation in meaningful units. The mediation models were estimated using the brm function from the *brms* package (Bürkner, 2017) in R with the default, flat prior. Intervals around the path estimates are 95% credibility intervals from the posterior distribution.

Results

Manipulation Checks

Here we tested whether the self and social experimental conditions increased self and social relevance, respectively, compared to the control condition. As expected, the self condition elicited higher self-relevance ratings compared to the control condition (b = 12.41, 95% CI [10.02, 14.79], and the social condition elicited higher social relevance ratings than the control condition (b = 8.90, 95% CI [6.82, 10.99]). We also found that the self condition increased social relevance ratings and the social condition increased self-relevance ratings (Figure 4A; Table 5).

Condition Effects by Sharing Type

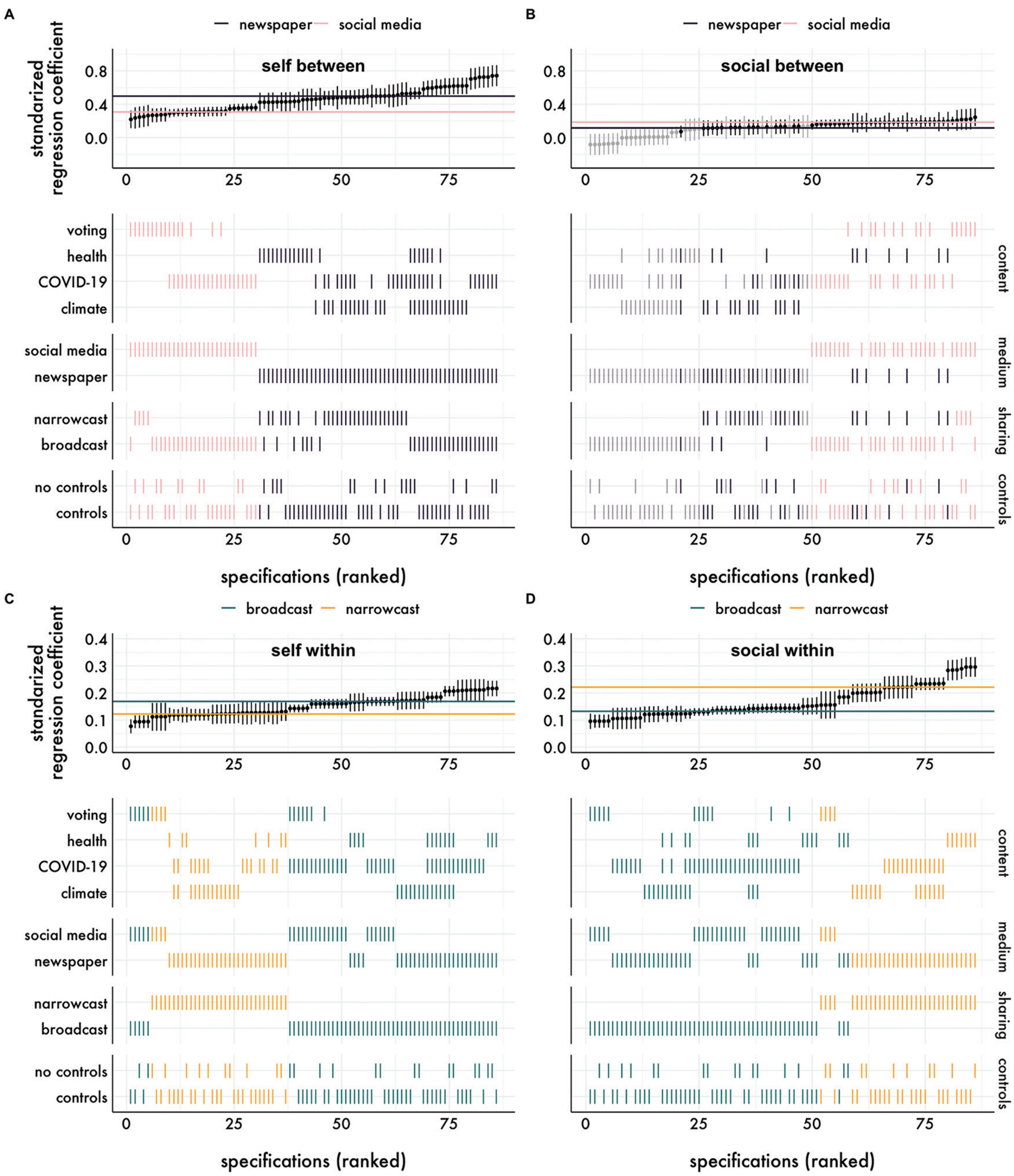
Next, we tested whether the experimental conditions increased sharing intentions. As expected, both the self (b = 5.23, 95% CI [3.57, 6.89]) and social (b = 3.37, 95% CI [1.70, 5.05]) experimental conditions were associated with stronger broadcast sharing intentions than the control condition (Figure 4B; Table 6). Directly comparing whether the effects differed as a function of sharing type revealed that the social condition had a stronger effect on narrowcasting compared to broadcasting (b = 3.53, 95% CI [1.25, 5.80]) as predicted. Although we hypothesized that the self condition would have a stronger effect on broadcasting compared to narrowcasting, this was not the case. Instead, there was a nonsignificant effect in the opposite direction (b = 2.08, 95% CI [−0.18, 4.35]).

Mediation

Finally, we tested whether the effects of the experimental conditions on sharing intentions were mediated by within-person changes in self and social relevance. For the self condition (Figure 5A), 60% of the total effect on broadcast sharing intentions was mediated by changes in self-relevance and 32% was mediated by changes in social relevance; 38% of the total effect on narrowcast sharing intentions was mediated by changes in self-relevance and 51% was mediated by changes in social relevance. For the social condition (Figure 5B), 35% of the total effect on broadcast sharing intentions was mediated by changes in self-relevance and 67%

Figure 3

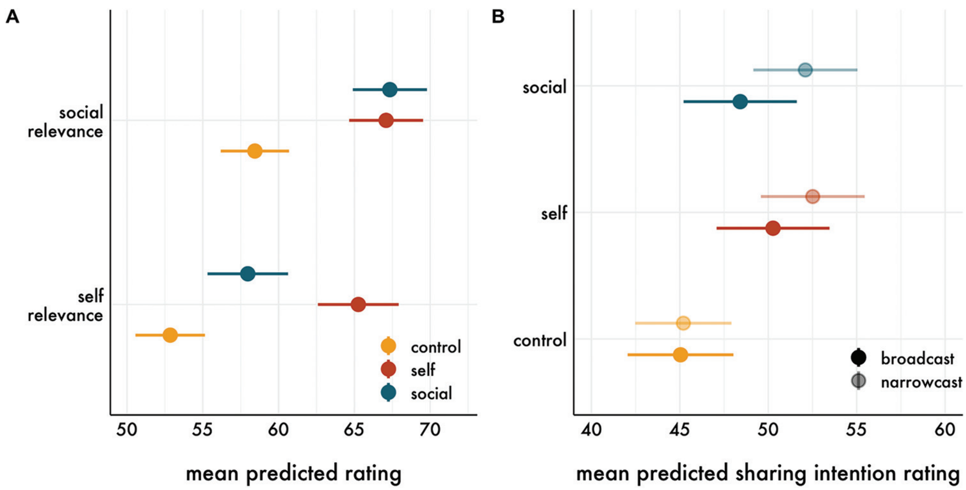
Specification Curve Visualizing the Relationships Between Sharing Intentions and (A) Between-Person Self-Relevance, (B) Between-Person Social Relevance, (C) Within-Person Self-Relevance, and (D) Within-Person Social Relevance, Across Analytic Decisions and Subsets of the Data



Note. The top panels depict the relationship between the relevance variables and sharing intentions. Each dot represents the standardized regression coefficient for the relevance variable of interest from a unique model specification with a 95% confidence interval around it. Model specifications are ordered by the regression coefficient; models for which the regression coefficient of interest was statistically significant at $p < .05$ are visualized in black, whereas coefficients $p > .05$ are in gray. The colored horizontal lines represent the median regression coefficient across model specifications for each relevance variable, separately. The bottom panels show the analytic decisions that were included in each model specification. Model specifications for between-person variables (A & B) are colored based on message medium, whereas they are colored based on sharing type for within-person variables (C & D). Models for which the regression coefficient of interest was statistically significant at $p < .05$ are visualized are opaque, whereas coefficients $p > .05$ are partially opaque. Content = content type; medium = message medium; sharing = sharing type; controls = inclusion of demographic covariates. See the online article for the color version of this figure.

Figure 4

(A) Manipulation Check: Mean Predicted Self and Social Relevance Ratings as a Function of Experimental Condition (Self, Social, or Control). (B) Effects of Self- and Social-Relevance on Sharing: Mean Predicted Sharing Intention Ratings as a Function of Experimental Condition and Sharing Type (Broad- or Narrowcasting)



Note. Error bars are 95% confidence intervals. See the online article for the color version of this figure.

was mediated by changes in social relevance; 9% of the total effect on narrowcast sharing intentions was mediated by changes in self-relevance and 54% was mediated by changes in social relevance.

Discussion

Information transmission within social networks supports widespread attitudinal and behavioral change. The perceived self and social relevance of the information are two psychological factors that may increase the value of sharing information with others. Across six studies including a wide variety of messages about pressing and potentially polarizing societal issues—COVID-19, voting, general health, and climate change—we found robust positive correlational relationships between message self and social relevance, and sharing intentions, both within- and between-person. Correlationally, self-relevance was more strongly related to intentions to share on with a wide audience (broadcasting) than directly with individual people (narrowcasting), whereas social relevance was more strongly related to narrowcasting intentions. The specification curve analysis indicated that these relationships generalized across message content and medium, and were not systematically affected by the inclusion of demographic variables. Finally, the preregistered experimental study provided evidence that self and social relevance are causally related to sharing intentions. Within-person mediation analyses showed clear specificity for the strength of the mediation effects. Consistent with prior theorizing (Barasch & Berger, 2014), the causal effect of the self manipulation on broadcasting was more strongly mediated by self than to social relevance, whereas the effect of the social manipulation on narrowcasting was more strongly mediated by social than self-relevance. However, our data also support the idea that self- and social-relevance are related to one another, such that manipulating one increases the other. Together, these findings extend existing models of information sharing, highlight self and social relevance as important sources of value that motivate sharing, and suggest that self and social relevance can be targeted by interventions to promote information sharing across various contexts.

Self and Social Relevance Are Each Robustly Related to Sharing Intentions

Disaggregating within- and between-person relationships indicated that (a) people who think messages are more self and socially relevant

Table 5

Results From the Manipulation Check Models

Model	Condition	*b* [95% CI]	*d*	*df*	*t*	*p*
Self-relevance	Control (intercept)	52.85 [50.55, 55.14]	—	396.00	45.13	<.001
	Self vs. Control	12.41 [10.02, 14.79]	1.36	225.44	10.19	<.001
	Social vs. Control	5.12 [2.97, 7.27]	0.64	212.74	4.67	<.001
Social relevance	Control (intercept)	58.44 [56.19, 60.69]	—	396.00	50.88	<.001
	Self vs. Control	8.66 [6.62, 10.69]	1.10	228.12	8.32	<.001
	Social vs. Control	8.90 [6.82, 10.99]	1.13	220.99	8.38	<.001

Note. Coefficients are in raw, unstandardized units. Degrees of freedom (*df*) were calculated using the Satterthwaite approximation. The reference group for condition is control.

Table 6
Results From the Experimental Condition by Sharing Type Model

Parameter	*b* [95% CI]	*d*	*df*	*t*	*p*
Control condition (intercept)	45.04 [42.05, 48.03]	—	431.34	29.54	<.001
Self vs. Control condition	5.23 [3.57, 6.89]	0.14	7,536.07	6.16	<.001
Social vs. Control condition	3.37 [1.70, 5.05]	0.09	7,535.21	3.95	<.001
Sharing type	0.16 [−1.49, 1.81]	0.01	743.49	0.19	.850
Self Condition × Sharing Type	2.08 [−0.18, 4.35]	0.04	6,961.88	1.81	.070
Social Condition × Sharing Type	3.53 [1.25, 5.80]	0.07	6,926.66	3.04	<.001

Note. Coefficients are in raw, unstandardized units. Degrees of freedom (*df*) were calculated using the Satterthwaite approximation. The reference group is control for condition and broadcasting for sharing type.

also tend to report higher sharing intentions, and (b) when people perceive messages as more self and socially relevant, they tend to report higher intentions to share them. The direction of these relationships was consistent across different message content domains, mediums, and sharing audiences. With the exception of a set of models estimating the relationship between broadcast sharing intentions and between-person social relevance including newspaper articles about COVID-19 in Study 5, the regression coefficients in all model specifications in the specification curve analysis were positive, indicating strong consistency. Although previous studies did not distinguish within- and between-person relationships, these findings are consistent with the value-based virality model, which posits self and social relevance as key factors in decisions to share (Scholz et al., 2017). They also demonstrate that despite being intimately intertwined (Ellemers et al., 2002; Harter, 1999; Scholz, Baek, et al., 2020), self and social relevance each contribute uniquely as well to sharing intentions.

Experimentally Manipulating Self and Social Relevance Increases Sharing Intentions

Extending these correlational findings, we observed evidence that self and social relevance are causally related to sharing intentions. Reflecting on both the self and social relevance of messages increased sharing intentions, compared to a control condition. This affirms the potential of self and social relevance frames as viable intervention targets to promote sharing behavior. We examined the underlying mechanism of these interventions using within-person mediation analyses, including perceived self and social relevance as parallel mediators. Consistent with prior work highlighting the dual roles of self and social relevance in sharing behavior (Scholz, Baek, et al., 2020), sharing intentions were partially mediated through both self and social relevance in all models. These results demonstrate that reflecting on the self and social relevance of content can increase sharing behavior through multiple pathways without altering the content of the messages.

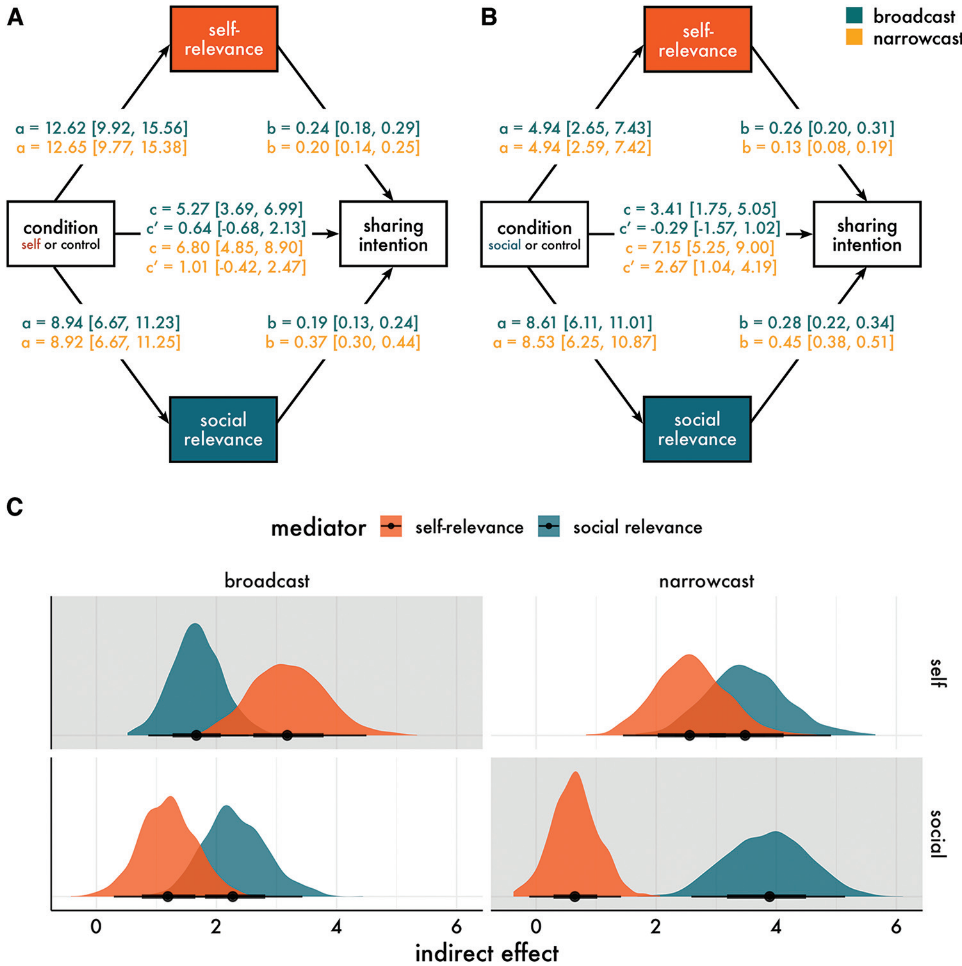
Relative Contributions of Self and Social Relevance Depend on the Sharing Context

Previous research has suggested that various motives affect decisions to share (Cappella et al., 2015; Lee & Ma, 2012) and their relative importance depends on the sharing context (Barasch & Berger, 2014). In the correlational analyses, self-relevance was more strongly related to broadcast compared to narrowcast sharing intentions, whereas the opposite was true for social relevance. This is in line with theoretical models emphasizing self-expression and enhancement as motives when sharing broadly and other-focused motives, such as helping and connecting, when sharing narrowly (Barasch & Berger, 2014). However, both self and social relevance were positively and uniquely related to broad- and narrowcast sharing intentions suggesting that they are both implicated in sharing regardless of context. The within-person mediation analyses further support this idea. There were indirect effects of the experimental manipulations on sharing intentions through both self and social relevance, but that their relative strength differed by the audience size. Specifically, the proportion of the causal effect of the self-manipulation on broadcasting was mediated more strongly (∼2x) for self compared to social relevance, and the proportion of the causal effect of the social manipulation on narrowcasting was mediated more strongly (∼6x) for social compared to self-relevance. Together, these findings are consistent with models that treat self-related and social motives as parallel processes that both contribute to sharing decisions, but to differing degrees depending on the sharing target (Scholz, Baek, et al., 2020).

Limitations and Future Directions

Despite notable strengths, such as the inclusion of large samples of people and messages, assessment of generalizability on several dimensions, and the use of correlational and causal methods, there are several limitations. First, all data were collected online. Concerns about data quality are mitigated by the relatively strict quality assurance procedures (detailed in the online supplementary material) used in these studies. Second, we did not recruit nationally or internationally representative samples. Our sample included participants from at least 49 states and was similar to the composition of adults in the United States with respect to age. However, our sample included more men, had a higher proportion of people who identified as White and Asian, and a lower proportion who identified as Black or African American, and as Hispanic or Latinx than the United States as a whole. Our sample also reported higher educational attainment and lower household incomes than the United States as a whole. Although the specification curve analysis showed that inclusion of these demographic variables did not systematically alter the strength of the relationships, future work should be designed to explicitly examine demographic, cross-national, political, and cross-cultural influences. Third, these studies focused on self-reported sharing intentions. Intentions are important precursors of behavior (Albarracin et al., 2021), but it would be useful to test these relationships in the context of actual sharing behavior. Fourth, although we experimentally manipulated self and social relevance and examined mediation within-person, it is possible that unmeasured variables influenced the observed

Figure 5
Results From the Bayesian Mediation Analyses



Note. (A-B) Path diagrams of the within-person multilevel mediation models for the (A) self condition and (B) social condition. Parameter estimates and bootstrapped 95% credible intervals are reported for broadcast and narrowcast sharing intentions separately. c = total effect (direct + indirect effect of condition on sharing intention); c′ = direct effect. (C) Posterior distributions for the indirect effects of the self (top panel) and social (bottom panel) conditions on broadcast (left panel) and narrowcast (right panel) sharing intentions. The gray panels highlight where the relationships between self and social relevance and sharing intentions are expected theoretically to be most differentiable. Indirect effects were calculated as a*b + cov(a, b). The point intervals represent the median of the posterior distribution, and the 66% and 95% credible intervals around the median. See the online article for the color version of this figure.

results. Finally, these analyses do not take into account individual differences, such as political orientation or social network configuration, or message properties, such as emotionality or concreteness, that might moderate the relationships between self and social relevance and sharing intentions. These are important future directions and we have shared the messages used in these studies to enable other researchers to explore message-level characteristics in these data.

Conclusions and Translational Implications

Across six studies, including nearly 31,000 message ratings about critical societal issues, we demonstrated correlational and causal evidence that perceived message self and social relevance are positively related to intentions to share content online. We conducted these analyses in ways that promote replicability and generalizability in order to maximize the translational potential of these findings, including: preregistering our hypotheses and analysis plans in Studies 5 and 6, aggregating across studies using the least constrained random effects structure possible, exploring the stability of the relationships using specification curve analysis, and using experimental manipulation to test causal relationships. Overall, this work suggests multiple viable routes to increasing information transmission, including: recruiting individuals who perceive the content as self or socially relevant to serve as messengers, tailoring messages to be more self or socially relevant to individuals, and intervening to draw attention to message self or social relevance without changing the message content itself, similar to recent interventions that shift attention to information accuracy to decrease sharing misinformation (Andı & Akesson, 2021; Pennycook et al., 2021). Such message framing approaches are particularly promising as scalable interventions since they only require a message and a prompt to reflect on relevance, and such prompts could readily be offered (e.g., by activists, government agencies, news organizations) to promote information sharing and catalyze action (Barberá et al., 2015). Together, this work extends existing theories of information sharing and provides compelling evidence that self and social relevance are important psychological factors that influence decisions to share information that can be leveraged to promote attitudinal and behavioral change.

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