Message self and social relevance increases intentions to share content: Correlational and causal evidence from six studies

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Abstract

Information transmission within social networks is crucial for widespread attitudinal and behavioral change. We propose that the value of sharing information increases when people perceive messages as more relevant to themselves and to people they know, resulting in stronger intentions to share. Six online studies (N participants = 3,727; messages = 362; message ratings = 30,954) showed robust evidence that perceived message self and social relevance are positively related to sharing intentions. Correlationally, self and social relevance were uniquely related to sharing intentions, both within- and between-person. Specification curve analysis revealed that the direction of these relationships were consistent across message content, medium, and sharing audience. A preregistered experiment showed that manipulating the self and social relevance of messages causally increased sharing intentions compared to a control condition. These findings 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, influence, virality

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). But what are the sources of this value and how might they be leveraged to promote information sharing? Bringing together insights from psychology, neuroscience, and marketing, we test the hypotheses that when people see information as being relevant to themselves and to people in their networks, these sources of value motivate them to share with others.

Sharing as a value-based decision

Decisions to share information can be thought of as a particular case of value-based decision making (Falk & Scholz, 2018; Scholz, Jovanova, et al., 2020), which involves selecting choice options based on their relative value. Within this framework, the perceived costs and benefits of each choice option are implicitly and explicitly weighed and integrated into a common currency—subjective value—that enables comparison between choice options (Levy & Glimcher, 2012). In line with this, neuroscientific research has shown 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. With respect to sharing, disparate inputs to the value computation, such as properties of the information (Berger & Milkman, 2012), the individual's implicit motives and explicit goals (Barasch & Berger, 2014; Berger, 2014), and perceived consequences of sharing (Scholz, Jovanova, et al., 2020), are expected to be integrated during valuation to form an expected value of sharing, which in turn determines whether or not the information is shared. However, not all inputs to this value calculation are equally amenable to intervention. In this paper, we focus on sources of subjective value that can be targeted to promote sharing behavior.

Self and social relevance

Two inputs to the valuation process that feature prominently in psychological theories of persuasion and social influence are the perceived self-relevance and social relevance—the perceived relevance to other people within the person's network—of the information (for a review, see (Falk & Scholz, 2018; Scholz, Jovanova, et al., 2020). Information that is related to the self is expected to have higher subjective value than information not relevant to the self for several reasons. First, there are well-documented egocentric biases in which individuals tend to pay greater attention to (Humphreys & Sui, 2015), process information more efficiently (Markus, 1977; Meyer & Lieberman, 2018), and over-value things and attributes perceived as being related to the self (Beer & Hughes, 2010; Kahneman et al., 1991; Mezulis et al., 2004; Taylor & Brown, 1988). Second, self-relevance encompasses an individuals' goals, values, desires, and motivations, which are closely tied to behavior (Markus, 1983). Third, there is substantial overlap between brain regions supporting self-referential processing and valuation (Beer et al., 2010; Berkman et al., 2017; D'Argembeau, 2013; Pfeifer & Berkman, 2018; Pfeifer & Peake, 2012), 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; Vijayakumar et al., 2020).

Social relevance is also hypothesized to increase subjective value. Humans have a fundamental need to belong (Baumeister & Leary, 1995) and can connect by sharing information. Sharing information is associated with activity in the brain's reward and valuation systems (Tamir et al., 2015). To effectively connect, individuals need to consider their audience and what they believe to be relevant to them in order to tailor their communication appropriately (Berger, 2014; Echterhoff et al., 2009; Higgins, 1992). This ability is supported by the tendency to spontaneously consider and predict the mental states of others (Blakemore, 2008; Koster-Hale & Saxe, 2013; Mildner & Tamir, 2021; Saxe, 2006; Saxe & Wexler, 2005; Thornton et al., 2018). 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 will 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). Deriving hypotheses from this model, we focus on explicit reports of self and social relevance and test correlational and causal relationships with intentions to share information that varies with respect to content, medium, and audience.

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 pressing and important societal issues (messages N = 362; message ratings N = 30,954), and assessed the generalizability of these relationships with respect to message content (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 sharing audience (Barasch & Berger, 2014; Scholz, Baek, et al., 2020), we also examined generalizability to broadcast and narrowcast sharing. Broadcasting is sharing information with a large and often ill-defined group of individuals (e.g. via social media), whereas narrowcasting is sharing information with one or a small group of well-defined individuals (e.g. via a direct message).

It is unclear whether the relationships between self and social relevance and sharing are driven by message-induced responses (i.e., message that are perceived as relatively more self and/or socially relevant) or by individual differences in the propensity to view content as self and/or socially relevant. Therefore, we distinguished within- and between-person relationships between self and social relevance and sharing intentions using multilevel modeling. Given the rich dataset, we pooled the raw data across studies in a mega-analysis (Eisenhauer, 2021; Steinberg et al., 1997) to precisely estimate effect sizes. We also examined the robustness of these relationships across alternative model specifications and within specific subsets of the data using specification curve analysis. In addition to these integrated analyses, we present analyses for each study individually in Supplementary Material for completeness. Studies 1-4 used existing data, whereas Studies 5 and 6 were preregistered before collecting data (https://osf.io/bgs5y/registrations). 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.

Table 1
Overview of studies

Study	N	Content	Medium	Sharing type	Type
Study 1	2081	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*	315	COVID-19 & climate change	Newspapers	Broad- & narrowcast	Correlational
Study 6*	397	Health & climate change	Newspapers	Broad- & narrowcast	Correlational & causal

Note. Study 1 combines data from four samples from the same project. *Preregistered study

Correlational analyses

Methods

Participants

These analyses included data from six online studies (N = 3,727) and participants were 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% non-binary or third gender, 0.2% idenfitied 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 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 either COVID-19, voting, general health, or climate change (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. The messages used in this study are available online (https://osf.io/nfr7h/). 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 Supplementary Material for study-specific details. Responses were standardized (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. 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, Brockhoff, & Chris-tensen, 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). Additional software packages used to conduct these analyses in R include: *boot* (Version 1.3-24; Canty & Ripley, 2019), *dplyr* (Version 1.0.7; Wickham et al., 2021), *forcats* (Version 0.5.1; Wickham, 2021), *furrr* (Version 0.2.2; Vaughn & Dancho, 2021), *ggplot2* (Version 3.3.5; Wickham, 2019), *ggpubr* (Version 0.4.0; Kassambara, 2020), *kableExtra* (Version 1.3.1; Zhu, 2020), *knitr* (Version 1.31; Xie, 2021), *Matrix* (Version 1.2-18; Bates & Maechler, 2019), *purrr* (Version 0.3.4; Henry & Wickham, 2020), *readr* (Version 1.4.0; Wickham & Hester, 2020), *report* (Version 0.3.5; Makowski et al., 2020), *stringr* (Version 1.4.0; Wickham, 2019), *tibble* (Version 3.1.2; Müller & Wickham, 2021), *tidyr* (Version 1.1.3; Wickham, 2021), and *tidyverse* (Wickhman, 2019).

Mega-analysis. We used a mega-analysis approach ((Eisenhauer, 2021; Steinberg et al., 1997) 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 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 variables included in the mega-analysis 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 Supplementary Material; the results did not change appreciably from those reported in the main manuscript.

Specification curve analysis. We complemented the mega-analysis using 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 manuscript 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 7 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; see 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 (Giudice & Gangestad, 2021), we conceptualize this set of analytic decisions as uncertain ("Type-U") because the decision options are not clearly equivalent or non-equivalent, 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).

Table 2
Means, standard deviations, and repeated measures correlations for each study

Study	Variable	Range	*M (SD)*	*r* [95% CI]		
				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.

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 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 [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 ($\beta_{interaction}$ = -0.10, 95% CI [-0.13, -0.07]). 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.

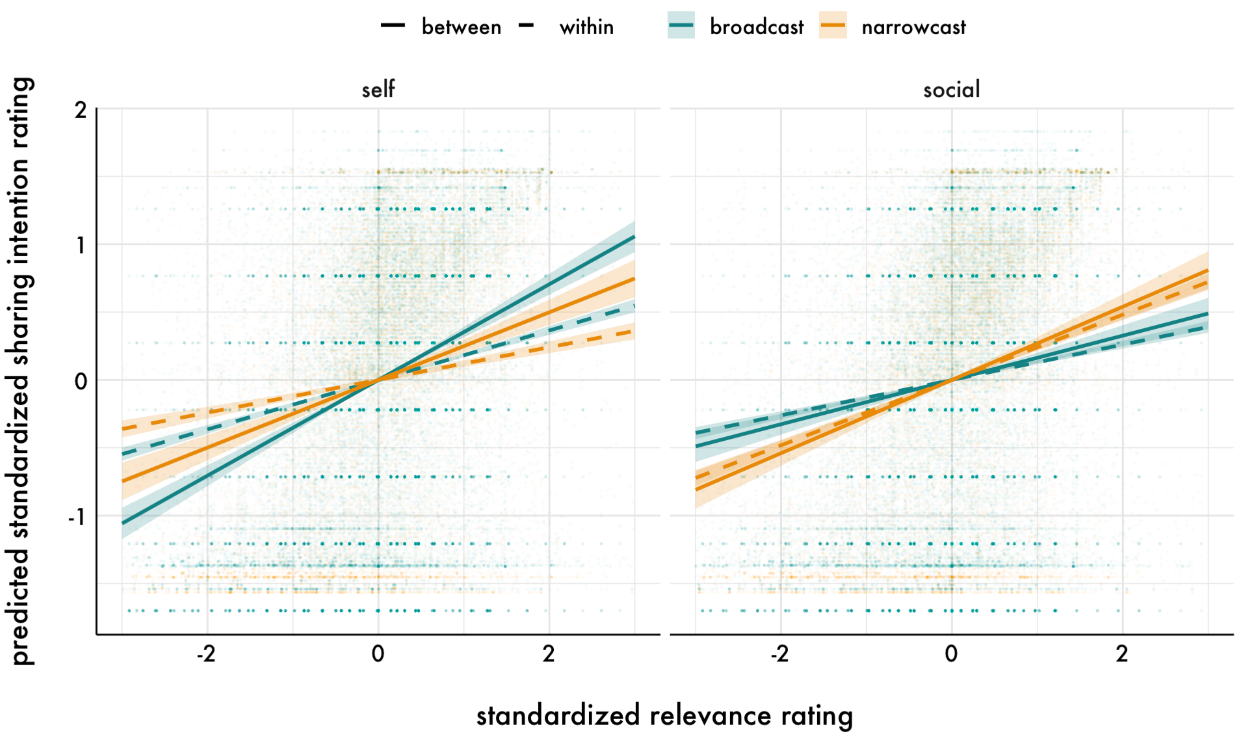

Figure 1. The predicted within- and between-person relationships for relevance ratings and sharing intention ratings from the mega-analysis as a function of within- and between-person relevance variable (self or social) and sharing type (broad- or narrowcasting). The points represent the raw (i.e., not 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.

Table 3
Results from the mega-analysis model of predictors of sharing intentions

Parameter	β [95% CI]	*df*	*t*	*p*
Sharing type	-0.00 [-0.01, 0.01]	23772.62	0.01	.990
Self between	0.35 [0.31, 0.39]	3776.06	17.94	< .001
Self within	0.18 [0.17, 0.20]	325.24	22.16	< .001
Social between	0.16 [0.12, 0.20]	3743.23	8.33	< .001
Social within	0.13 [0.12, 0.14]	287.62	17.49	< .001
Self between x Sharing type	-0.10 [-0.13, -0.07]	23690.57	7.08	< .001
Self within x Sharing type	-0.06 [-0.08, -0.04]	13738.55	6.57	< .001
Social between x Sharing type	0.11 [0.08, 0.14]	23694.57	7.30	< .001
Social within x Sharing type	0.11 [0.09, 0.13]	11895.65	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.

Specification curve analysis

Overall, 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 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) showed that this was due to negative coefficients from models of broadcasting newspaper articles about COVID-19 (Study 5) and non-significant coefficients from models of broadcasting newspaper articles about climate change (Studies 5 and 6). Across relevance variables, these relationships were not systematically altered by the inclusion of demographic covariates.

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). 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).

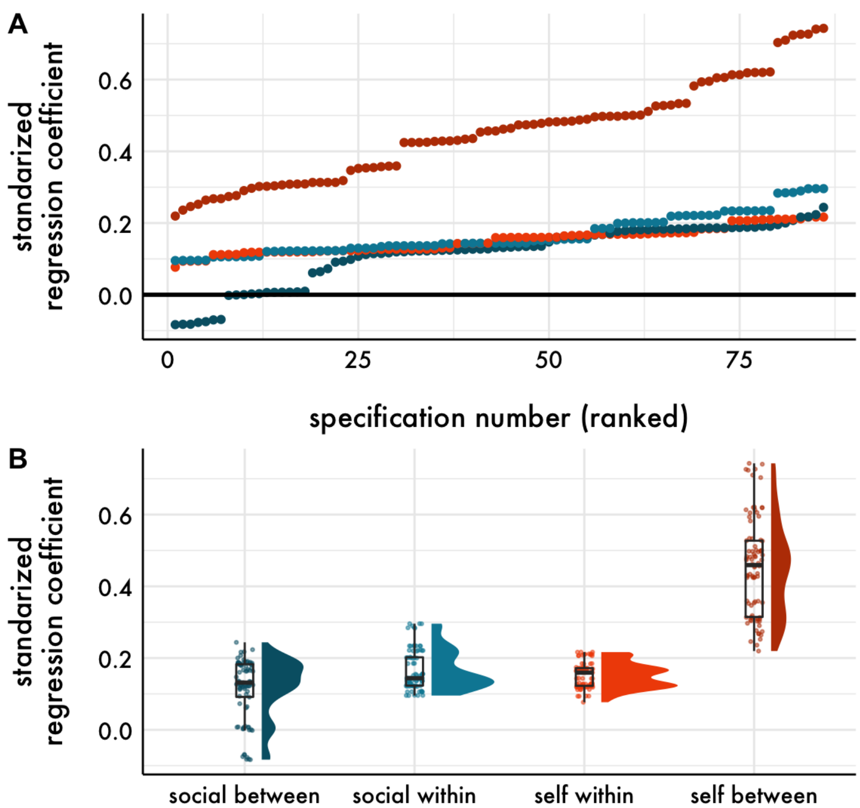

Figure 2. Specification curve comparison. (A) The top panel shows separate specification curves for each relevance variable. Within each curve, models are ordered by the magnitude of the standardized regression coefficient. (B) The bottom panel shows the distribution of standardized regression coefficients 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.

Table 4

Specification curve descriptives statistics

Parameter	Median β	β Range	Positive & significant	Negative & significant
Self between	0.46	0.22, 0.74	100.00%	0.00%
Self within	0.16	0.08, 0.22	100.00%	0.00%
Social between	0.13	-0.08, 0.24	63.95%	0.00%
Social within	0.14	0.10, 0.30	100.00%	0.00%

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

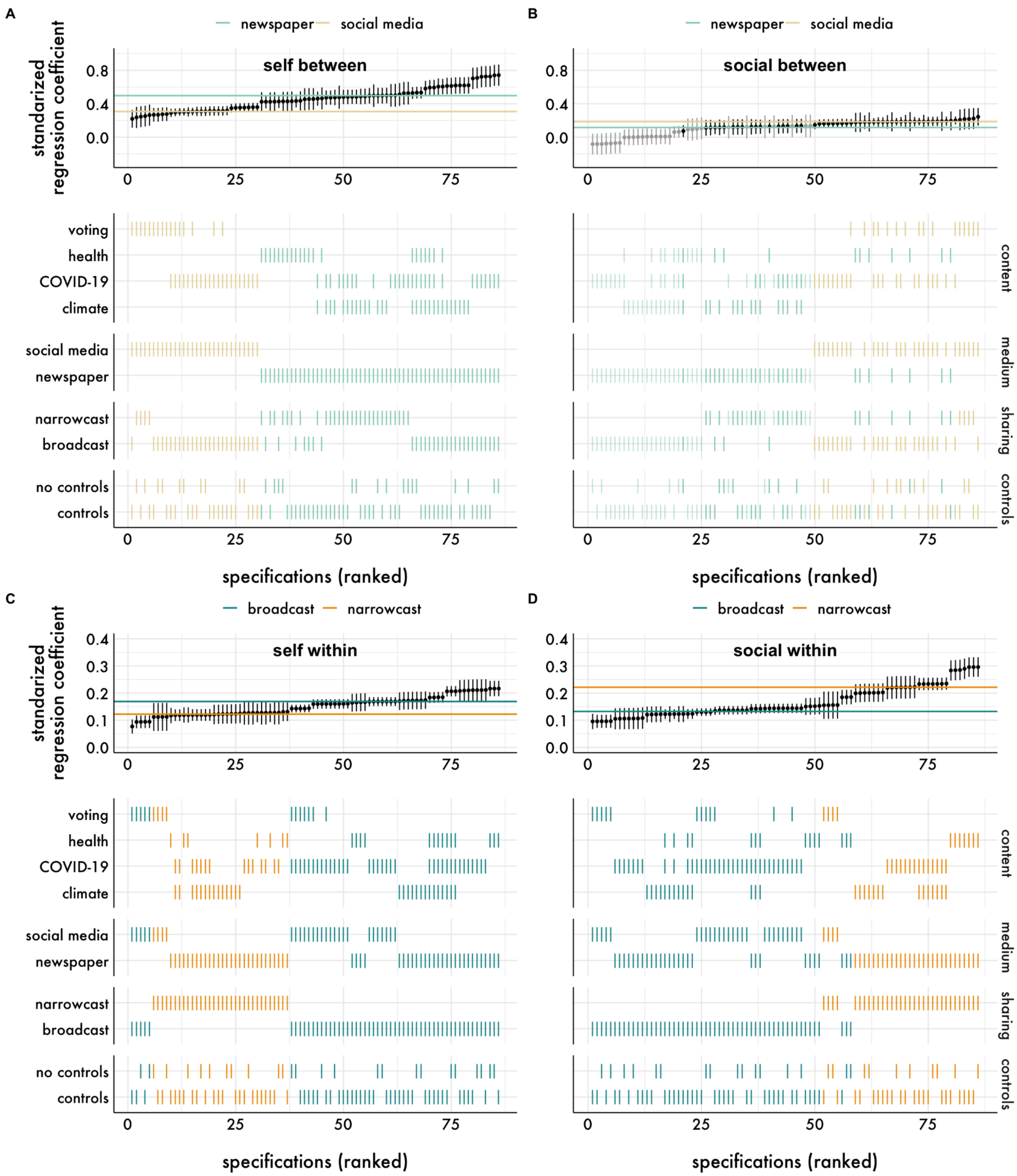

Figure 3. Specification curve visualizing the relationships between sharing intentions and (A) between-person self relevance, (B) between-person social relevance, (C) within-person self relevance, and (D) within-person social relevance, across analytic decisions and subsets of the data. The top panels 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 $p < 0.05$ are visualized are opaque, whereas coefficients $p > 0.05$ are partially opaque. Content = content type; medium = message medium; sharing = sharing type; controls = inclusion of demographic covariates.

Causal study analyses

In the previous analyses, we found robust positive correlations between self and social relevance and intentions to share content that generalized across message content and medium. Here, we extend these 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.

Methods

Participants

This preregistered study (https://osf.io/r4jwa) 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 (https://osf.io/25swg/). 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 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 or social condition. We used a mixed design in which all participants saw a set of 5 messages in the control condition and a set of 5 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. These messages were sampled from a pool of 55 articles per topic and each participant was randomized to one of 11 sets of articles that contained 5 messages about health and 5 about climate change, matched with respect to the web traffic the news article has generated (specifically, the number of click-throughs for the article URL). For each message, participants wrote a comment based on the experimental condition and rated self ("This message is relevant to me") and social relevance ("This message is relevant to people I know") using a 100-point scale (0 = strongly disagree, 100 = strongly agree), as well as their broadcast intention to share on social media ("I would share this article by posting on social media (on Facebook, Twitter, etc)") and narrowcast intention to share directly with someone ("I would share this article directly with someone I know (via email, direct message, etc)") using a 100-point scale (0 = strongly disagree, 100 = strongly agree).

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). Finally, we estimated four within-person mediation models (http://www.page-gould.com/r/indirectmlm/) testing the degree to which the effect of the experimental condition (self v. control, or social v. control) on sharing intentions was mediated by self-relevance in the self condition or social relevance in the social condition, estimating these models separately for broadcasting and narrowcasting. The raw units were retained here (versus standardizing) to facilitate interpretation in meaningful units. Bootstrapping was used to generate 95% confidence intervals.

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).

Table 5
Results from the manipulation check models

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

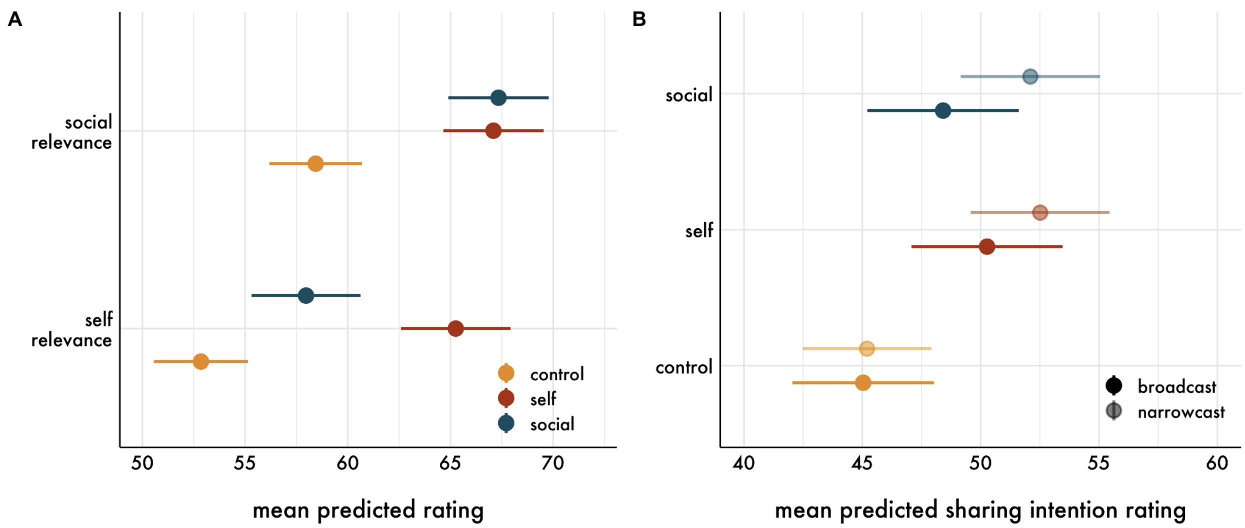

Figure 4. (A) Manipulation check: Mean predicted self and social relevance ratings as a function of experimental condition (self, social, or control). (B) Effects of self- and social-relevance on sharing: Mean predicted sharing intention ratings as a function of experimental condition and sharing type (broad- or narrowcasting). Error bars are 95% confidence intervals.

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 non-significant effect in the opposite direction (b = 2.08, 95% CI [-0.18, 4.35]).

Table 6
Results from the experimental condition by sharing type model

Parameter	*b* [95% CI]	*df*	*t*	*p*
Control condition (intercept)	45.04 [42.05, 48.03]	431.34	29.54	< .001
Self v. Control condition	5.23 [3.57, 6.89]	7536.07	6.16	< .001
Social v. Control condition	3.37 [1.70, 5.05]	7535.21	3.95	< .001
Sharing type	0.16 [-1.49, 1.81]	743.49	0.19	.850
Self condition x Sharing type	2.08 [-0.18, 4.35]	6961.88	1.81	.070
Social condition x Sharing type	3.53 [1.25, 5.80]	6926.66	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.

Mediation

Finally, we tested whether the positive relationships between experimental condition and sharing intentions were mediated by within-person changes in relevance. For the self condition (Figure 5A), 82.15% of the total effect was mediated by changes in self-relevance for broadcast sharing intentions, and 75.67% was mediated by changes in self-relevance for narrowcast sharing intentions. A similar pattern was observed for the social condition (Figure 5B); 118.51%[1] of the total effect was mediated by changes in social relevance for broadcast sharing intentions, and 66.24% was mediated by changes in social relevance for narrowcast sharing intentions.

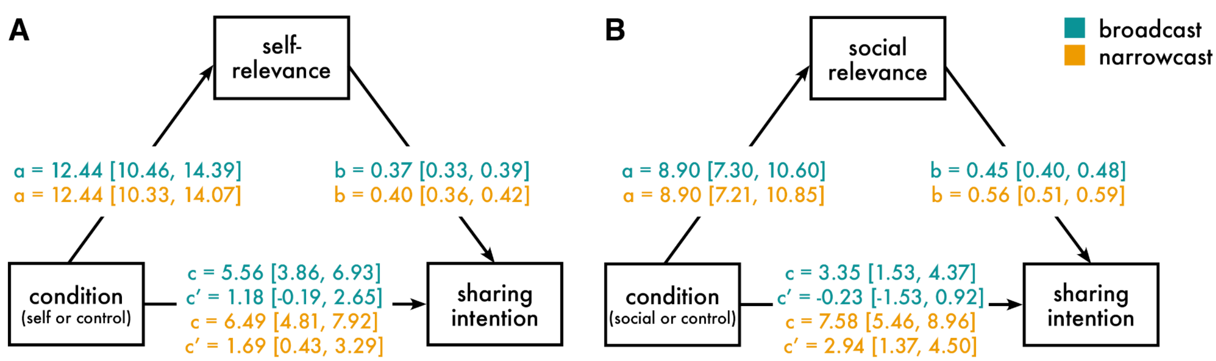

Figure 5. Path diagrams of the within-person multilevel mediation models for the (A) self condition and (B) social condition. Parameter estimates and bootstrapped 95% confidence intervals are reported for broadcast and narrowcast sharing intentions separately. c = total effect (direct + indirect effect of condition on sharing intention); c′ = direct effect.

Discussion

Information transmission within social networks is crucial for widespread attitudinal and behavioral change within a society. The perceived self and social relevance of the information are two psychological factors that can increase the value of sharing information with others, and their relative importance may differ depending on the sharing audience (Barasch & Berger, 2014; Scholz, Baek, et al., 2020). Across six studies including a wide variety of different

[1] The percent of the total effect mediated can exceed 100% when suppression is present and this occurs roughly half the time when a true association is completely mediated due to sampling error (Shrout & Bolger, 2002).

messages (N = 371), we found robust positive correlational relationships between self-reported message self and social relevance, and sharing intentions, both within- and between-person. The mega-analysis showed that self-relevance was more strongly related to intentions to share on social media (broadcasting) than directly with individual people (narrowcasting), whereas social relevance was more strongly related to intentions to narrowcast. The specification curve analysis indicated that these relationships generalized across message contents and were not systematically affected by the inclusion of demographic control variables. Finally, the preregistered experimental study provided evidence that self and social relevance are causally related to sharing intentions. Together, these findings suggest that self and social relevance can be targeted by interventions to promote information sharing across various contexts.

Self and social relevance are separately and robustly related to sharing intentions

Disaggregating within- and between-person relationships indicated that 1) people who tend to think messages are more self and socially relevant also tend to report higher sharing intentions, and 2) when people perceive messages as more self and socially relevant (relative to each person's own baseline), they also tend to report higher intentions to share them. The direction of these relationships were 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 from Study 5, the regression coefficients in all model specifications in the specification curve analysis were positive, indicating strong consistency.

With respect to magnitude, these analyses highlighted systematic dissociations between self and social relevance. For example, the relationship between broadcast sharing intentions and between-person self-relevance tended to be stronger for newspaper articles than social media messages, whereas the relationship with between-person social relevance tended to be weaker for newspaper articles and stronger for social media messages.

Although previous studies did not distinguish within- and between-person relationships, these findings are consistent with the model of value-based virality which posits self and social relevance as key inputs in decisions to share (Falk & Scholz, 2018; Scholz et al., 2017), and with observations that neural activation in brain regions supporting self-referential processing and social cognition is positively associated with sharing intentions (Baek et al., 2017; Scholz, Baek, et al., 2020). These findings are also consistent with previous qualitative reports that self-relevance plays an important role in virality (Botha & Reyneke, 2013). In this study, we also demonstrated that although self and social relevance are intimately intertwined (Ellemers et al., 2002; Harter, 1999), they are separable constructs that are each uniquely related to sharing intentions. Together, these results suggest that both these psychological factors are considered during decisions to share information (Scholz, Baek, et al., 2020).

Experimentally manipulating self and social relevance increases sharing intentions

Extending these correlational findings, we also 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, and these effects were mediated through increased perceptions of self or social relevance, respectively.

This demonstrates that self and social relevance are viable intervention targets to promote sharing behavior, and that this can be achieved without altering the content of the messages.

Interestingly, there was an asymmetry in the degree to which the experimental manipulation increased self and social relevance. In line with previous work showing egocentric biases in information processing (Humphreys & Sui, 2015; Markus, 1977; Mezulis et al., 2004), reflecting on the self-relevance of a message increased both self and social relevance perceptions, whereas reflecting on social relevance primarily increased perceived message social relevance. More specifically, the self condition strongly increased perceived message self-relevance and also increased perceived social relevance to a similar degree as the social condition, whereas the social condition increased perceived self-relevance, but to a lesser degree than the self condition. That is, what we perceive as relevant to us, we think is relevant to others, but what we perceive as relevant to others we don't necessarily think is relevant to us.

Relative contributions of self and social relevance depend on the sharing target

Previous research has suggested that various motives affect decisions to share (Berger, 2014; Cappella et al., 2015; Lee & Ma, 2012) and their relative importance depends on the context and who a person is sharing with (Barasch & Berger, 2014; Dubois et al., 2016). Here, we observed that 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 that emphasize self-expression and enhancement as important motives when sharing broadly and that other-focused motives, such as helping and connecting, are important when sharing narrowly (Barasch & Berger, 2014; Dubois et al., 2016). However, both self and social relevance were uniquely and positively related to broad- and narrowcast sharing intentions suggesting that they are both implicated in sharing regardless of sharing audience. This is 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 message, assessment of generalizability on several dimensions, and the use of both correlational and causal methods, these results should be interpreted in light of several limitations. First, all of these data were collected online. Although participants were primarily MTurk workers, we also included a sample of college students. Concerns about data quality are mitigated by the relatively strict quality assurance procedures (detailed in Supplementary Material) used in these studies. Second, we did not recruit nationally or internationally, representative samples. Across studies, our sample included participants from at least 49 states and is relatively similar to adults in the United States with respect to age. However, compared to the U.S. population our sample included more men, and had a slightly higher proportion of people who identified as White and Asian, and a slightly lower proportion of people who identified as Black or African American, and as Hispanic or Latina/Latino/Latinx. Our sample also reported higher educational attainment and lower household incomes than the U.S. population. Although the specification curve analysis showed that inclusion of these demographic variables did not systematically alter the strength of the relationships, future work addressing individual differences should be designed to explicitly examine demographic, as well as cross-national and cross-cultural influences. Third, these studies focused on self-reported sharing intentions rather than actual sharing behavior. Although intentions are important precursors of behavior (Albarracin et al., 2021), it would be useful to test these relationships in additional, ecologically valid contexts, for example by asking participants to actually share the articles on social media or with someone they know. Fourth, although we experimentally manipulated self and social relevance and examined mediation within-person, it is possible that unmeasured variables influenced the observed results. Fifth, we did not conduct message-level analyses to identify message properties that are related to self and social relevance, and sharing intentions. Given the wide variability of the message-level correlations between self and social relevance reported in Supplementary Material and the positive relationships between self and social relevance and intentions to share content, future research might seek to identify message properties that tend to be related to stronger correlations between self and social relevance. Finally, the specification curve analyses suggested that between-person self-relevance tended to be more strongly related to sharing intentions for newspaper articles, whereas this relationship was stronger for between-person with social media messages. Since these analyses were exploratory, this hypothesis should be tested explicitly in future studies.

Conclusions and translational implications

Integrating across six studies, we demonstrated correlational and causal evidence that perceived message self and social relevance are positively related to intentions to share. 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 in the mega-analysis and using the least constrained random effects structure possible, exploring the stability of the relationships using specification curve analysis, and experimentally manipulating self and social relevance to test causal relationships with sharing intentions. Overall, this work indicates that 1) people who tend to perceive messages as self and socially relevant are more likely to share them, 2) when messages that are perceived as more self or socially relevant, they are more likely to be shared, and 3) reflecting on self and social relevance can increase the perceived self and social relevance and hence likelihood of sharing. These findings suggest 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, 2020; Pennycook et al., 2021). Together, this work 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.

Author contributions

All authors developed the concepts for one or more of the individual studies reported. Authors DC, CS, HC, BPD, SB, and EBF drafted the preregistrations for Study 5 and/or Study 6. Authors DC, HC, BPD, PP, JC-T, NC, and AP collected the data. DC performed the data analysis and interpretation with supervision from EBF. DC drafted the manuscript and all authors provided critical revisions. All authors approved the final version of the manuscript for submission.

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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, 6 authors self-identified as women and 4 authors as men. With respect to race and ethnicity, 1 author self-identified as Chinese, 1 author as South Asian, 7 authors as White, and 1 author as White Hispanic. With respect to age, all authors are 40 years old or younger.

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., 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 the first and last authors of our current paper), our references contain 22% woman(first)/woman(last), 13% man/woman, 35% woman/man, and 30% 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, non-binary, or transgender people.

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References

Albarracin, D., Sunderrajan, A., McCulloch, K. C., & Jones, C. (2021). Mistaking an Intention for a Behavior: The Case of Enacting Behavioral Decisions Versus Simply Intending to Enact Them. Personality and Social Psychology Bulletin, 47(3), 455–467. https://doi.org/10.1177/0146167220929203

Andı, S., & Akesson, J. (2020). Nudging Away False News: Evidence from a Social Norms Experiment. Digital Journalism, 9(1), 1–21. https://doi.org/10.1080/21670811.2020.1847674

Baek, E. C., Scholz, C., O'Donnell, M., & Falk, E. B. (2017). The Value of Sharing Information: A Neural Account of Information Transmission. Psychological Science, 28(7). https://doi.org/10.1177/0956797617695073

Bakdash, J. Z., & Marusich, L. R. (2017). Repeated Measures Correlation. Frontiers in Psychology, 8, 456. https://doi.org/10.3389/fpsyg.2017.00456

Barasch, A., & Berger, J. (2014). Broadcasting and Narrowcasting: How Audience Size Affects What People Share. Journal of Marketing Research, 51(3), 286–299. https://doi.org/10.1509/jmr.13.0238

Barberá, P., Wang, N., Bonneau, R., Jost, J. T., Nagler, J., Tucker, J., & González-Bailón, S. (2015). The Critical Periphery in the Growth of Social Protests. PLOS ONE, 10(11), e0143611. https://doi.org/10.1371/journal.pone.0143611

Bates, D. & Maechler, M. (2019). Matrix: Sparse and Dense Matrix Classes and Methods. R package version 1.2-18. https://CRAN.R-project.org/package=Matrix

Bates, D., Maechler, M., Bolker, B., & Walker, S. (2015). Fitting Linear Mixed-Effects Models Using lme4. Journal of Statistical Software, 67(1), 1-48. https://doi.org/10.18637/jss.v067.i01.

Baumeister, R. F., & Leary, M. R. (1995). The Need to Belong: Desire for Interpersonal Attachments as a Fundamental Human Motivation. Psychological Bulletin, 117(3), 497–529. https://doi.org/10.1037/0033-2909.117.3.497

Beer, J. S., & Hughes, B. L. (2010). Neural systems of social comparison and the "above-average" effect. NeuroImage, 49(3), 2671–2679. https://doi.org/10.1016/j.neuroimage.2009.10.075

Beer, J. S., Lombardo, M. V., & Bhanji, J. P. (2010). Roles of Medial Prefrontal Cortex and Orbitofrontal Cortex in Self-evaluation. Journal of Cognitive Neuroscience, 22(9), 2108–2119. https://doi.org/10.1162/jocn.2009.21359

Berger, J. (2014). Word of mouth and interpersonal communication: A review and directions for future research. Journal of Consumer Psychology, 24(4), 586–607. https://doi.org/10.1016/j.jcps.2014.05.002

Berger, J., & Milkman, K. L. (2012). What Makes Online Content Viral? Journal of Marketing Research, 49(2), 192–205. https://doi.org/10.1509/jmr.10.0353

Berkman, E. T., Livingston, J. L., & Kahn, L. E. (2017). Finding The "Self" in Self-Regulation: The Identity-Value Model. Psychological Inquiry, 28(2–3), 77–98. https://doi.org/10.1080/1047840x.2017.1323463

Bertolero, M. A., Dworkin, J. D., David, S. U., Lloreda, C. L., Srivastava, P., Stiso, J., Zhou, D., Dzirasa, K., Fair, D. A., Kaczkurkin, A. N., Marlin, B. J., Shohamy, D., Uddin, L. Q., Zurn, P., & Bassett, D. S. (2020). Racial and ethnic imbalance in neuroscience reference lists

and intersections with gender. BioRxiv, 2020.10.12.336230. https://doi.org/10.1101/2020.10.12.336230
Blakemore, S.-J. (2008). The social brain in adolescence. Nature Reviews Neuroscience, 9(4), 267–277. https://doi.org/10.1038/nrn2353
Botha, E., & Reyneke, M. (2013). To share or not to share: the role of content and emotion in viral marketing. Journal of Public Affairs, 13(2), 160–171. https://doi.org/10.1002/pa.1471
Canty, A., & Ripley, B. (2019). boot: Bootstrap R (S-Plus) Functions. R package version 1.3-24.
Caplar, N., Tacchella, S., & Birrer, S. (2017). Quantitative evaluation of gender bias in astronomical publications from citation counts. Nature Astronomy, 1(6), 0141. https://doi.org/10.1038/s41550-017-0141
Cappella, J. N., Kim, H. S., & Albarracín, D. (2015). Selection and Transmission Processes for Information in the Emerging Media Environment: Psychological Motives and Message Characteristics. Media Psychology, 18(3), 396–424. https://doi.org/10.1080/15213269.2014.941112
Chatterjee, P., & Werner, R. M. (2021). Gender Disparity in Citations in High-Impact Journal Articles. JAMA Network Open, 4(7), e2114509. https://doi.org/10.1001/jamanetworkopen.2021.14509
D'Argembeau, A. (2013). On the Role of the Ventromedial Prefrontal Cortex in Self-Processing: The Valuation Hypothesis. 7. https://doi.org/10.3389/fnhum.2013.00372
Dion, M. L., Sumner, J. L., & Mitchell, S. M. (2018). Gendered Citation Patterns across Political Science and Social Science Methodology Fields. Political Analysis, 26(3), 312–327. https://doi.org/10.1017/pan.2018.12
Doré, B. P., Scholz, C., Baek, E. C., Garcia, J. O., O'Donnell, M. B., Bassett, D. S., Vettel, J. M., & Falk, E. B. (2019). Brain Activity Tracks Population Information Sharing by Capturing Consensus Judgments of Value. Cerebral Cortex, 29(7), 3102–3110. https://doi.org/10.1093/cercor/bhy176
Dubois, D., Bonezzi, A., & Angelis, M. (2016). Sharing with Friends versus Strangers: How Interpersonal Closeness Influences Word-of-Mouth Valence. Journal of Marketing Research, 53(5), 712–727. https://doi.org/10.1509/jmr.13.0312
Dworkin, J. D., Linn, K. A., Teich, E. G., Zurn, P., Shinohara, R. T., & Bassett, D. S. (2020). The extent and drivers of gender imbalance in neuroscience reference lists. Nature Neuroscience, 23(8), 918–926. https://doi.org/10.1038/s41593-020-0658-y
Echterhoff, G., Lang, S., Krämer, N., & Higgins, E. T. (2009). Audience-Tuning Effects on Memory: The Role of Audience Status in Sharing Reality. Social Psychology, 40(3), 150–163. https://doi.org/10.1027/1864-9335.40.3.150
Eisenhauer, J. G. (2021). Meta-analysis and mega-analysis: A simple introduction. Teaching Statistics, 43(1), 21–27. https://doi.org/10.1111/test.12242
Ellemers, N., Spears, R., & Doosje, B. (2002). SELF AND SOCIAL IDENTITY*. Annual Review of Psychology, 53(1), 161–186. https://doi.org/10.1146/annurev.psych.53.100901.135228
Falk, E. B., Berkman, E. T., & Lieberman, M. D. (2012). From Neural Responses to Population Behavior. Psychological Science, 23(5), 439–445. https://doi.org/10.1177/0956797611434964

Falk, E. B., & Scholz, C. (2018). Persuasion, Influence, and Value: Perspectives from Communication and Social Neuroscience. Annual Review of Psychology, 69(1), 1–28. https://doi.org/10.1146/annurev-psych-122216-011821

Fulvio, J. M., Akinnola, I., & Postle, B. R. (2021). Gender (Im)balance in Citation Practices in Cognitive Neuroscience. Journal of Cognitive Neuroscience, 33(1), 3–7. https://doi.org/10.1162/jocn_a_01643

Genevsky, A., & Knutson, B. (2015). Neural Affective Mechanisms Predict Market-Level Microlending. Psychological Science, 26(9), 1411–1422. https://doi.org/10.1177/0956797615588467

Giudice, M. D., & Gangestad, S. W. (2021). A Traveler's Guide to the Multiverse: Promises, Pitfalls, and a Framework for the Evaluation of Analytic Decisions. Advances in Methods and Practices in Psychological Science, 4(1), 251524592095492. https://doi.org/10.1177/2515245920954925

Harter, S. (1999). The Construction of the Self: A Developmental Perspective. Guilford Publications.

Henry, L., & Wickham, H. (2020). purrr: Functional Programming Tools. R package version 0.3.4. https://CRAN.R-project.org/package=purrr

Higgins, E. T. (1992). Achieving "Shared Reality" in the Communication Game: A Social Action That Create; Meaning. Journal of Language and Social Psychology, 11(3), 107–131. https://doi.org/10.1177/0261927x92113001

Humphreys, G. W., & Sui, J. (2015). Attentional control and the self: The Self-Attention Network (SAN). Cognitive Neuroscience, 7(1–4), 5–17. https://doi.org/10.1080/17588928.2015.1044427

Kahneman, D., Knetsch, J. L., & Thaler, R. H. (1991). Anomalies: The Endowment Effect, Loss Aversion, and Status Quo Bias. Journal of Economic Perspectives, 5(1), 193–206. https://doi.org/10.1257/jep.5.1.193

Kassambara, A. (2020). ggpubr: 'ggplot2' Based Publication Ready Plots. R package version 0.4.0. https://CRAN.R-project.org/package=ggpubr

Koster-Hale, J., & Saxe, R. (2013). Theory of Mind: A Neural Prediction Problem. Neuron, 79(5), 836–848. https://doi.org/10.1016/j.neuron.2013.08.020

Kuznetsova, A., Brockhoff, P. B., & Christensen, R. H. B. (2017). "lmerTest Package:Tests in Linear Mixed Effects Models." Journal of Statistical Software, 82(13), 1-26. https://doi.org/10.18637/jss.v082.i13

Lee, C. S., & Ma, L. (2012). News sharing in social media: The effect of gratifications and prior experience. Computers in Human Behavior, 28(2), 331–339. https://doi.org/10.1016/j.chb.2011.10.002

Levy, D. J., & Glimcher, P. W. (2012). The root of all value: a neural common currency for choice. Current Opinion in Neurobiology, 22(6), 1027–1038. https://doi.org/10.1016/j.conb.2012.06.001

Makowski, D., Ben-Shachar, M.S., Patil, I. & Lüdecke, D. (2020). Automated Results Reporting as a Practical Tool to Improve Reproducibility and Methodological Best Practices Adoption. CRAN. Available from https://github.com/easystats/report

Maliniak, D., Powers, R., & Walter, B. F. (2013). The Gender Citation Gap in International Relations. International Organization, 67(4), 889–922. https://doi.org/10.1017/s0020818313000209
Markus, H. (1977). Self-schemata and processing information about the self. Journal of Personality and Social Psychology, 35(2), 63–78. https://doi.org/10.1037/0022-3514.35.2.63
Markus, H. (1983). Self-knowledge: An expanded view. Journal of Personality, 51(3), 543–565. https://doi.org/10.1111/j.1467-6494.1983.tb00344.x
Meyer, M. L., & Lieberman, M. D. (2018). Why People Are Always Thinking about Themselves: Medial Prefrontal Cortex Activity during Rest Primes Self-referential Processing. Journal of Cognitive Neuroscience, 30(5), 714–721. https://doi.org/10.1162/jocn_a_01232
Mezulis, A. H., Abramson, L. Y., Hyde, J. S., & Hankin, B. L. (2004). Is There a Universal Positivity Bias in Attributions? A Meta-Analytic Review of Individual, Developmental, and Cultural Differences in the Self-Serving Attributional Bias. Psychological Bulletin, 130(5), 711–747. https://doi.org/10.1037/0033-2909.130.5.711
Mildner, J. N., & Tamir, D. I. (2021). The People Around You Are Inside Your Head: Social Context Shapes Spontaneous Thought. Journal of Experimental Psychology: General. https://doi.org/10.1037/xge0001057
Mitchell, S. M., Lange, S., & Brus, H. (2013). Gendered Citation Patterns in International Relations Journals. International Studies Perspectives, 14(4), 485–492. https://doi.org/10.1111/insp.12026
Pennycook, G., Epstein, Z., Mosleh, M., Arechar, A. A., Eckles, D., & Rand, D. G. (2021). Shifting attention to accuracy can reduce misinformation online. Nature, 1–6. https://doi.org/10.1038/s41586-021-03344-2
Pfeifer, J. H., & Berkman, E. T. (2018). The Development of Self and Identity in Adolescence: Neural Evidence and Implications for a Value-Based Choice Perspective on Motivated Behavior. Child Development Perspectives, 12(3), 158–164. https://doi.org/10.1111/cdep.12279
Pfeifer, J. H., & Peake, S. J. (2012). Self-development: Integrating cognitive, socioemotional, and neuroimaging perspectives. 2(1). https://doi.org/10.1016/j.dcn.2011.07.012
Saxe, R. (2006). Uniquely human social cognition. Current Opinion in Neurobiology, 16(2), 235–239. https://doi.org/10.1016/j.conb.2006.03.001
Saxe, R., & Wexler, A. (2005). Making sense of another mind: The role of the right temporo-parietal junction. Neuropsychologia, 43(10), 1391–1399. https://doi.org/10.1016/j.neuropsychologia.2005.02.013
Scholz, C., Baek, E. C., O'Donnell, M., & Falk, E. B. (2020). Decision-making about broad- and narrowcasting: a neuroscientific perspective. Media Psychology, 23(1), 131–155. https://doi.org/10.1080/15213269.2019.1572522
Scholz, C., Baek, E. C., O'Donnell, M., Kim, H., Cappella, J. N., & Falk, E. B. (2017). A neural model of valuation and information virality. Proceedings of the National Academy of Sciences, 114(11), 2881–2886. https://doi.org/10.1073/pnas.1615259114
Scholz, C., Jovanova, M., Baek, E. C., & Falk, E. B. (2020). Media content sharing as a value-based decision. Current Opinion in Psychology, 31, 83–88. https://doi.org/10.1016/j.copsyc.2019.08.004

Schultz, P. W., Nolan, J. M., Cialdini, R. B., Goldstein, N. J., & Griskevicius, V. (2007). The Constructive, Destructive, and Reconstructive Power of Social Norms. Psychological Science, 18(5), 429–434. https://doi.org/10.1111/j.1467-9280.2007.01917.x

Simonsohn, U., Simmons, J. P., & Nelson, L. D. (2020). Specification curve analysis. Nature Human Behaviour, 4(11), 1208–1214. https://doi.org/10.1038/s41562-020-0912-z

Steegen, S., Tuerlinckx, F., Gelman, A., & Vanpaemel, W. (2016). Increasing Transparency Through a Multiverse Analysis. Perspectives on Psychological Science, 11(5), 702–712. https://doi.org/10.1177/1745691616658637

Steinberg, K. K., Smith, S. J., Stroup, D. F., Olkin, I., Lee, N. C., Williamson, G. D., & Thacker, S. B. (1997). Comparison of Effect Estimates from a Meta-Analysis of Summary Data from Published Studies and from a Meta-Analysis Using Individual Patient Data for Ovarian Cancer Studies. American Journal of Epidemiology, 145(10), 917–925. https://doi.org/10.1093/oxfordjournals.aje.a009051

Tamir, D. I., Zaki, J., & Mitchell, J. P. (2015). Informing Others Is Associated With Behavioral and Neural Signatures of Value. Journal of Experimental Psychology: General, 144(6), 1114–1123. https://doi.org/10.1037/xge0000122

Tamir, D. I., & Mitchell, J. P. (2012). Disclosing information about the self is intrinsically rewarding. 109(21). https://doi.org/10.1073/pnas.1202129109

Taylor, S. E., & Brown, J. D. (1988). Illusion and Well-Being: A Social Psychological Perspective on Mental Health. Psychological Bulletin, 103(2), 193–210. https://doi.org/10.1037/0033-2909.103.2.193

Thornton, M. A., Weaverdyck, M. E., & Tamir, D. I. (2018). The social brain automatically predicts others' future mental states. Journal of Neuroscience, 39(1), 1431–18. https://doi.org/10.1523/jneurosci.1431-18.2018

Vaughan, D. and Dancho, M. (2021). furrr: Apply Mapping Functions in Parallel using Futures. R package version 0.2.2. https://CRAN.R-project.org/package=furrr

Vijayakumar, N., Flournoy, J. C., Mills, K. L., Cheng, T. W., Mobasser, A., Flannery, J. E., Allen, N. B., & Pfeifer, J. H. (2020). Getting to know me better: An fMRI study of intimate and superficial self-disclosure to friends during adolescence. Journal of Personality and Social Psychology, 118(5), 885–899. https://doi.org/10.1037/pspa0000182

Wang, X., Dworkin, J., Zhou, D., Stiso, J., Falk, E. B., Zurn, P., Bassett, D. S., & Lydon-Staley, D. M. (n.d.). Gendered Citation Practices in the Field of Communication. https://doi.org/10.31234/osf.io/ywrcq

Wickham, H. & Hester, J. (2020). readr: Read Rectangular Text Data. R package version 1.4.0. https://CRAN.R-project.org/package=readr

Wickham, H. (2016) ggplot2: Elegant Graphics for Data Analysis. Springer-Verlag New York.

Wickham, H. (2019). stringr: Simple, Consistent Wrappers for Common String Operations. R package version 1.4.0. https://CRAN.R-project.org/package=stringr

Wickham, H. (2021). forcats: Tools for Working with Categorical Variables (Factors). R package version 0.5.1. https://CRAN.R-project.org/package=forcats

Wickham, H. (2021). tidyr: Tidy Messy Data. R package version 1.1.3. https://CRAN.R-project.org/package=tidyr

Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L. D. A., François, R., ... & Yutani, H. (2019). Welcome to the Tidyverse. Journal of open source software, 4(43), 1686. doi: https://doi.org/10.21105/joss.01686

Wickham, H., François, R., Henry, L., & Müller, K. (2021). dplyr: A Grammar of Data Manipulation. R package version 1.0.7. https://CRAN.R-project.org/package=dplyr

Yihui Xie (2021). knitr: A General-Purpose Package for Dynamic Report Generation in R. R package version 1.31.

Zhou, D., Cornblath, E. J., Stiso, J., Teich, E. G., Dworkin, J. D., Blevins, A. S., & Bassett, D. S. (2020). Gender diversity statement and code notebook v1.0. https://github.com/dalejn/cleanBib

Zhu, H. (2020). kableExtra: Construct Complex Table with 'kable' and Pipe Syntax. R package version 1.3.1. https://CRAN.R-project.org/package=kableExtra

Supplementary Material

Additional demographic information

Here, we report available demographic information collapsed across studies. Additional tables summarizing this information for each study separately is available online (https://cnlab.github.io/self-social-sharing/analysis/demographics). In Studies 1, 5, and 6 we also measured socioeconomic status using education and household incoming as indicators. With respect to education, participants reported the following as highest degree completed: 46.3% Bachelor's degree, 16.1% some college, 15.8% Master's degree, 9.9% Associate's degree, 8.7% high school graduate, 1.6% Doctorate degree, 1.4% Professional school degree, and 0.2% less than high school. With respect to household income, participants reported the following income brackets: 26.5% $50,000 - $74,999, 16.8% $75,000 - $99,999, 16.1% > $100,000, 15.1% $35,000 - $49,999, 10.1% $25,000 - $34,999, 6.5% $16,000 - $24,999, 3.2% $5,000 - $11,999, 2.8% $12,000 - $15,999, 1.3% < $5,000, and 1.6% not reported.

Study-specific participant information

Study 1. In this study, we used existing data from a project investigating the degree to which several message framing interventions might enhance message effectiveness and intentions, norms, and beliefs related to social distancing as a response to the COVID-19 pandemic. This project includes four sub-studies. For the purposes of this paper, the data were collapsed across message framing conditions, since our focus in this paper is on relationships between self and social-relevance and sharing. This study was conducted online through Amazon's Mechanical Turk (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 (SOP; https://osf.io/nx6aj/). To be consistent across studies reported in this manuscript, we deviated from the project SOP by not trimming outliers to +/- 3 SD. Of the 2470 participants initially recruited, participants were excluded if they failed the English comprehension question (n = 46), the attention screening (n = 291), knowledge questions about COVID-19 (n = 14), had invariant responses that were more than 3 SDs from the median (n = 13), or had more than one of these issues (n = 29). This yielded a final sample of 2081.

Study 2. This study used existing data from a project examining the effect of several message framing interventions on intentions to vote and perception of norms related to voting. For the purposes of this study, we collapse across message framing conditions, since our focus in this paper is on relationships between self and social-relevance and sharing. The 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, eligible to vote in the U.S. general election, and passed an initial attention screening question. Of the 632 participants initially recruited, participants were excluded if they failed the English comprehension question (n = 10), one or more attention check (n = 14), or had invariant responses that were more than 3 SDs from the median (n = 29; Med = 22.2%, SD = 21.3%), or for more than one of these reasons (n = 32). This yielded a final sample of N = 547.

Study 3. This study (N = 248) used existing data from a project on civic engagement in college students. The study was conducted online at the University of Pennsylvania.

Participants were included if they were adults 18 or older and eligible to vote in the United States. Participants were randomized to one of two message framing conditions, but for the purposes of this paper, the data were collapsed across conditions, since our focus in this paper is on relationships between self and social-relevance and sharing.

Study 4. This study used existing data from a project examining relationships between various message properties and broadcast sharing intentions using headlines from the New York Times. The study was conducted online through MTurk. Participants were included if they were adults 18 or older and were fluent in English. Of the 200 participants who completed the survey, 61 participants were excluded for failing one or more of the English comprehension questions. This yielded a final sample of *N* = 139.

Study 5. This preregistered study (https://osf.io/r4jwa) 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 (https://osf.io/25swg/). Sample size was based on a power analysis. We determined that with N = 300, we would have >80% power to detect an effect size of d = 0.05 for within-person effects and >95% power to detect an effect of d = 0.10 for within- and between-person effects. Of the 408 participants initially recruited, participants were excluded if they failed the English comprehension question (n = 15), one or more attention checks (n = 75), or the knowledge questions about COVID-19 (n = 15). This yielded a final sample of N = 315.

Study 6. This preregistered study (https://osf.io/vgcpq) was conducted online through MTurk. The same inclusion and exclusion criteria from Study 5 were used here (https://osf.io/25swg/). Sample size was based on a power analysis. We determined that with *N* = 420, we would have >80% power to detect an effect of d = 0.10 and >95% power to detect an effect of d = 0.15. Of the 644 participants initially recruited, participants were excluded if they failed the English comprehension question (n = 20), one or more attention checks (n = 80), or did not provide comprehensible text during the experimental manipulation (n = 233). This yielded a final sample of N = 397.

Study-specific procedures

Study 1. Participants were exposed to health messages about social distancing, framed as social media posts on Instagram. In three of the four sub-studies from this project, each participant was exposed to 5 messages drawn randomly from a pool of 15 messages. For the fourth sub-study, each participant saw the same 5 messages. For each message, participants rated self (“This message is relevant to me”) and social relevance (“This message is relevant to other people I know”), as well as their intention to share on social media (“I would share this message on social media”) using a 7-point scale (1 = strongly disagree, 7 = strongly agree).

Study 2. Participants were exposed to messages about voting, framed as social media posts for Twitter. Each participant was exposed to 5 messages about voting. For each message, they rated self (“This message is relevant to me”) and social relevance (“This message is relevant to people I know”), as well as their intention to share on social media (“I would share this message on social media”) using a 100-point scale (0 = strongly disagree, 100 = strongly agree).

Study 3. Participants were exposed to messages about voting, framed as social media posts for Instagram. Each participant was exposed to 5 messages about voting. For each message, they rated self ("This message is relevant to me") and social relevance ("This message is relevant to people I know"), as well as their broadcast intention to share on social media ("I would share this message on social media") and narrowcast intention to share directly with someone ("I would share this message directly with a friend") using a 100-point scale (0 = strongly disagree, 100 = strongly agree).

Study 4. Participants were exposed to messages (headline and brief abstract) about health from the New York Times. Each participant was exposed to 8 messages randomly drawn from a pool of 80 articles. For each message, they rated self ("How relevant is this content to you?") and social relevance ("How relevant is this content to other people?"), as well as their sharing intention ("How much would you want to share this article with other people?") using a 10-point scale (0 = not at all, 10 = very much).

Study 5. Participants were exposed to messages (headline and brief abstract) about COVID-19 or climate change from the New York Times (see Supplementary material for examples). Each participant was exposed to 10 messages, 5 about COVID-19 and 5 about climate change. Each participant was randomly assigned to one of 11 stimuli sets that included articles matched for popularity. For each message, they rated self ("This message is relevant to me") and social relevance ("This message is relevant to people I know") using a 100-point scale (0 = strongly disagree, 100 = strongly agree), as well as their broadcast intention to share on social media ("How much do you want to share this article by posting on your social media (on Facebook, Twitter, etc)?") and narrowcast intention to share directly with someone ("How much do you want to share this article directly with someone you know (via email, direct message, etc)?") using a 100-point scale (0 = not at all, 100 = very much).

Mega-analysis with downsampled data

Message-level correlations between self and social relevance. First, we conducted exploratory analyses looking at the correlation between self and social relevance for each message in each study. These correlations are visualized in Figure S1, and the average correlation strength and variability for each study and message content domain are reported in Table S1. The messages about climate change were used in both Study 5 and 6, but are treated separately for each study.

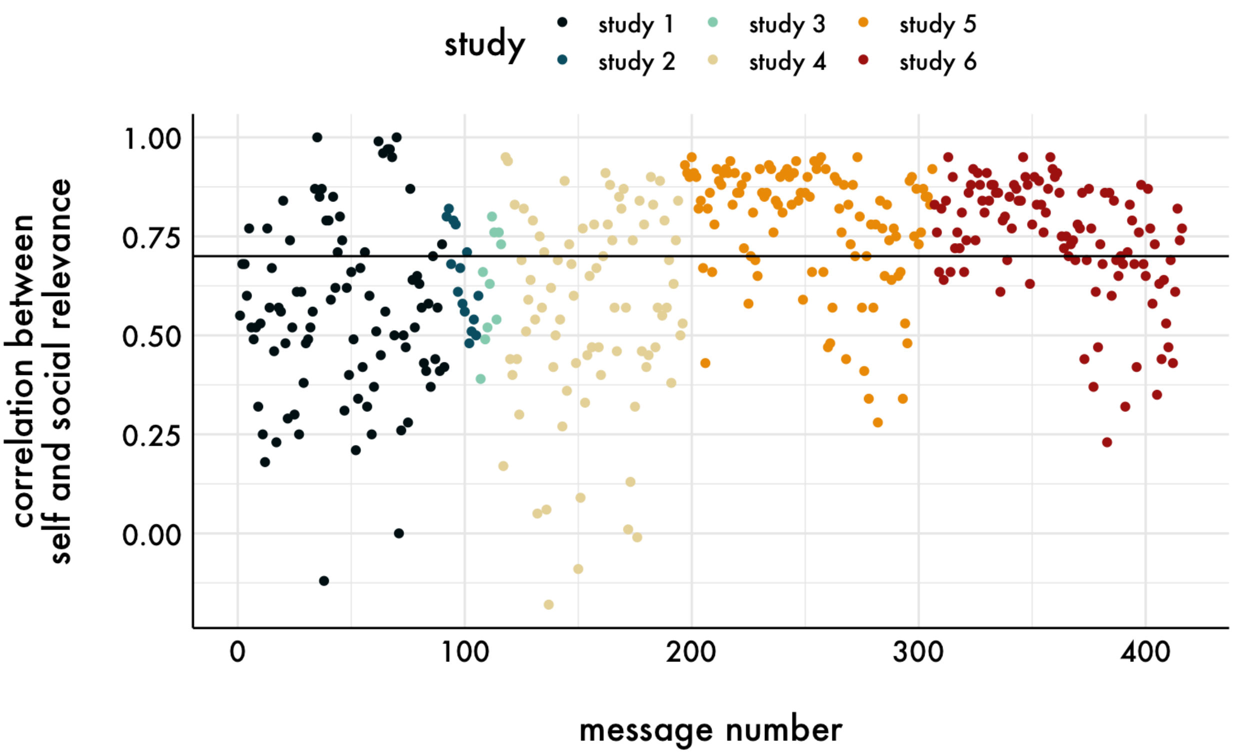

Figure S1. Message-level correlations between self and social relevance as a function of study. The horizontal line is r = .70 and is the cutoff used in the downsampled mega-analysis.

Table S1

Descriptive statistics about message-level correlations between self and social relevance as a function of study and content domain

Study	Content	Correlation *M*	Correlation *SD*	Correlation Range
Study 1	COVID-19	0.56	0.23	-0.12, 1.00
Study 2	Voting	0.64	0.12	0.48, 0.82
Study 3	Voting	0.63	0.14	0.39, 0.80
Study 4	Health	0.56	0.26	-0.18, 0.95
Study 5	Climate	0.84	0.11	0.43, 0.95
	COVID-19	0.73	0.17	0.28, 0.95
Study 6	Climate	0.82	0.09	0.61, 0.95
	Health	0.67	0.16	0.23, 0.88

Downsampled mega-analysis. Although the variance inflation factors (VIF) for the variables included in the mega-analysis reported in the main manuscript were small to moderate (VIF range = 1.00 - 4.24), we conducted a sensitivity analysis to assess the impact of multicollinearity on the model. Specifically, we estimated the same mega-analysis model reported in the main manuscript in a subset of the data that had message-level correlations below r = .70. This threshold for downsampling was selected as a benchmark because it means that half (49%) of the variance is shared between variables.

These results are consistent with those reported in the main manuscript (Figure S2; Table S2). All parameter estimates were in the same direction and did not deviate substantially with respect to magnitude from those in the original model (deviation range = 0.00 - 0.04). The largest deviation was for the interaction between sharing type and between-person self-relevance, such that the difference between broadcasting and narrowcasting decreased.

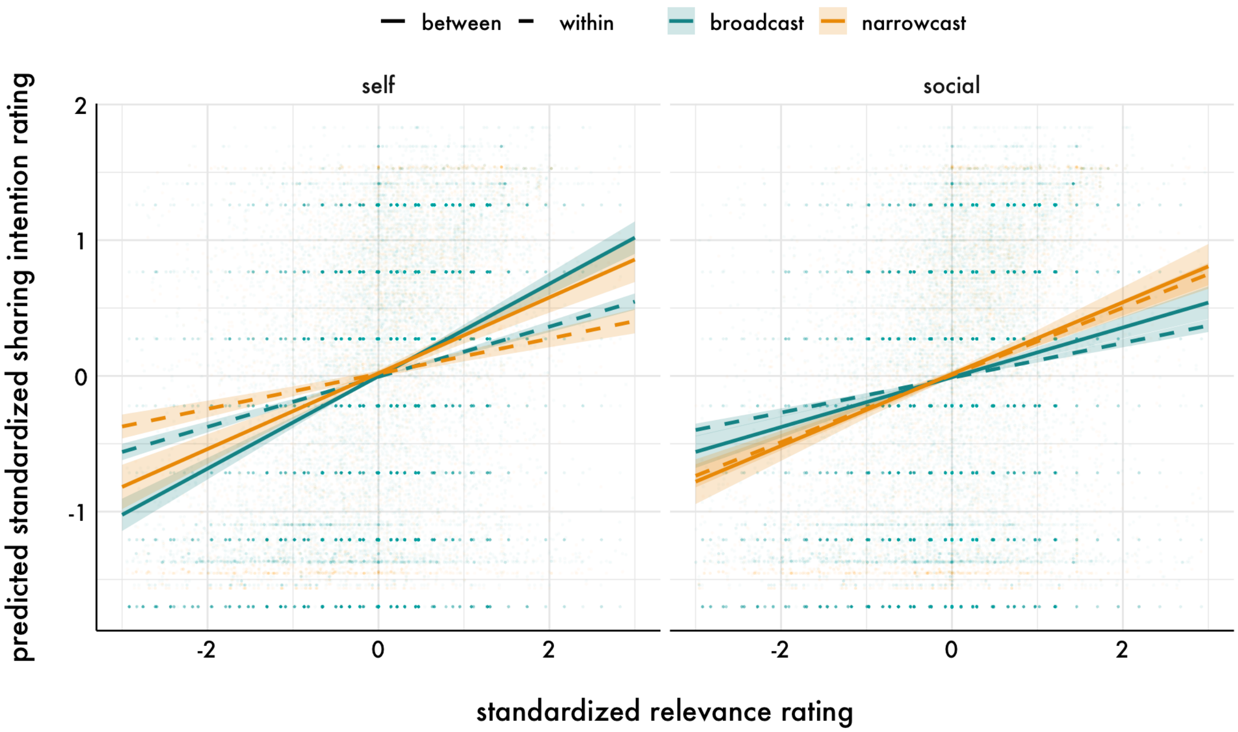

Figure S2. The predicted within- and between-person relationships for relevance ratings and sharing intention ratings from the mega-analysis as a function of within- and between-person relevance variable (self or social) and sharing type (broad- or narrowcasting) estimated from the downsampled data. The points represent the raw message-level responses; error bands are 95% confidence intervals. 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.

Table S2

Results from the downsampled mega-analysis model

Parameter	*β* [95% CI]	*df*	*t*	*p*
Sharing type	0.02 [-0.00, 0.04]	12764.56	1.54	.120
Self between	0.34 [0.30, 0.38]	3683.12	16.80	< .001
Self within	0.18 [0.16, 0.20]	136.37	18.01	< .001
Social between	0.18 [0.14, 0.22]	3653.76	9.08	< .001
Social within	0.13 [0.11, 0.14]	77.55	16.08	< .001
Self between x Sharing type	-0.06 [-0.10, -0.02]	12786.35	2.87	< .001
Self within x Sharing type	-0.06 [-0.08, -0.03]	5772.64	4.17	< .001
Social between x Sharing type	0.08 [0.04, 0.12]	12780.84	3.77	< .001
Social within x Sharing type	0.12 [0.09, 0.15]	3203.99	8.80	< .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.

Additional information about the specification curve analysis

As described in the main manuscript, the specification curve analysis explores the robustness of the relationships between self and social relevance and sharing intentions to inclusion of covariates and across different subsets of the data. Table S3 describes the 13 subsets that were included in the analysis. Figures S3-4 depict the curve for each relevance variable including a marker for which subset the model was estimated in. Descriptive statistics for the curve for each relevance variable separately is reported in Table S4 as a function of sharing type and message medium. Figure S5 includes all relevance variables in the same specification curve in order to compare them (versus showing the curve for each relevance variable separately in the main manuscript).

Table S3

Data subsets included in the specification curve analysis

Subset	Content	Medium	Sharing type	Studies	N models
1	COVID-19	Social media	Broadcast	1	28
2	COVID-19	Newspapers	Broadcast	5	28
3	COVID-19	Newspapers	Narrowcast	5	28
4	Voting	Social media	Broadcast	2 & 3	20
5	Voting	Social media	Narrowcast	3	16
6	Health	Newspapers	Broadcast	4 & 6	28
7	Health	Newspapers	Narrowcast	6	28
8	Climate change	Newspapers	Broadcast	5 & 6	28
9	Climate change	Newspapers	Narrowcast	5 & 6	28
10	COVID-19	Social media & newspapers	Broadcast	1 & 5	28
11	COVID-19 & voting	Social media	Broadcast	1, 2 & 3	28
12	COVID-19, health & climate change	Newspapers	Broadcast	4, 5 & 6	28
13	COVID-19 & climate change	Newspapers	Narrowcast	5 & 6	28

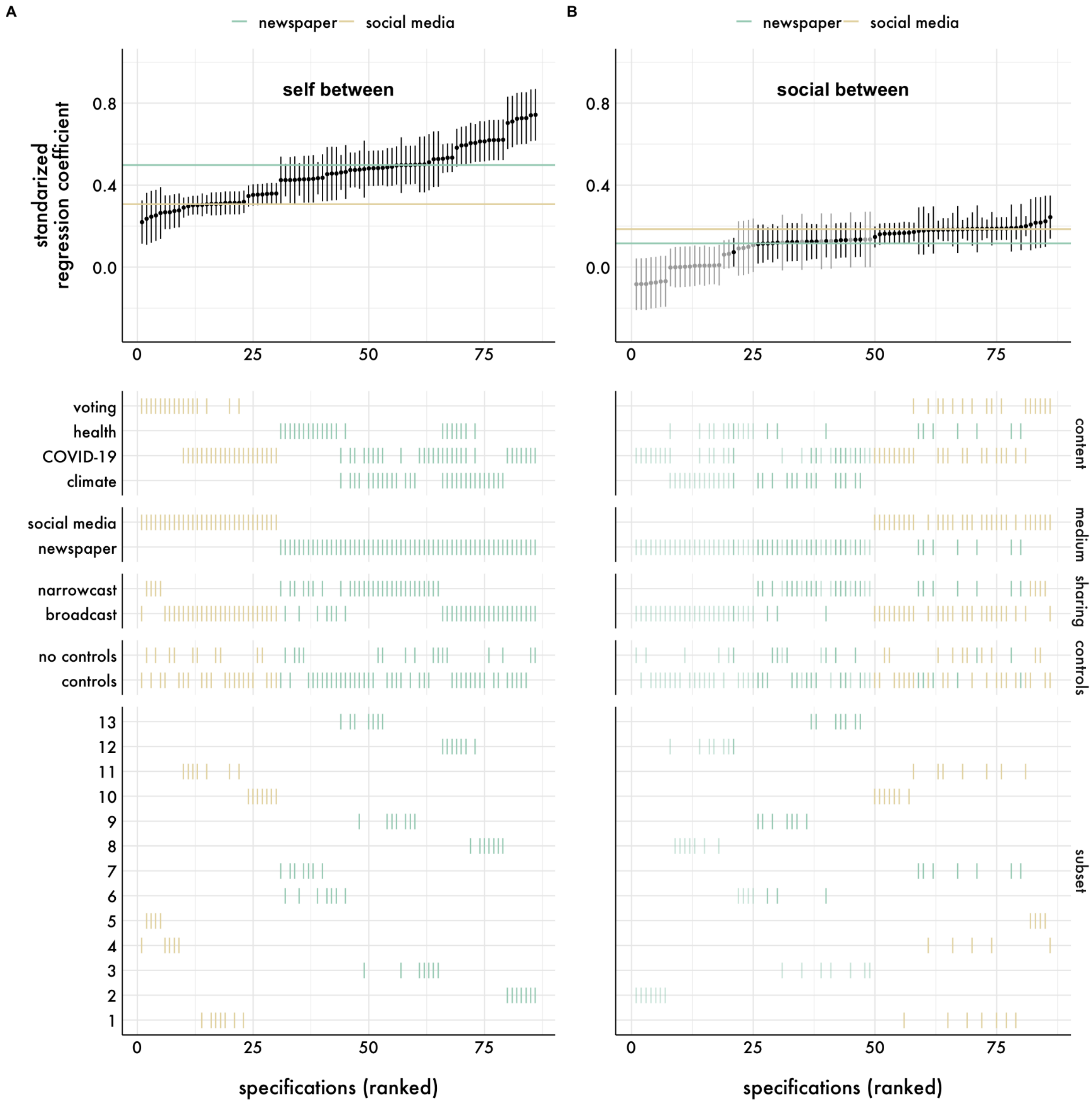

Figure S3. Specification curves for the between-person relevance variables reported in Figure 3A-B including an additional marker for which subset the model was estimated in. The subsets are described in Table S3.

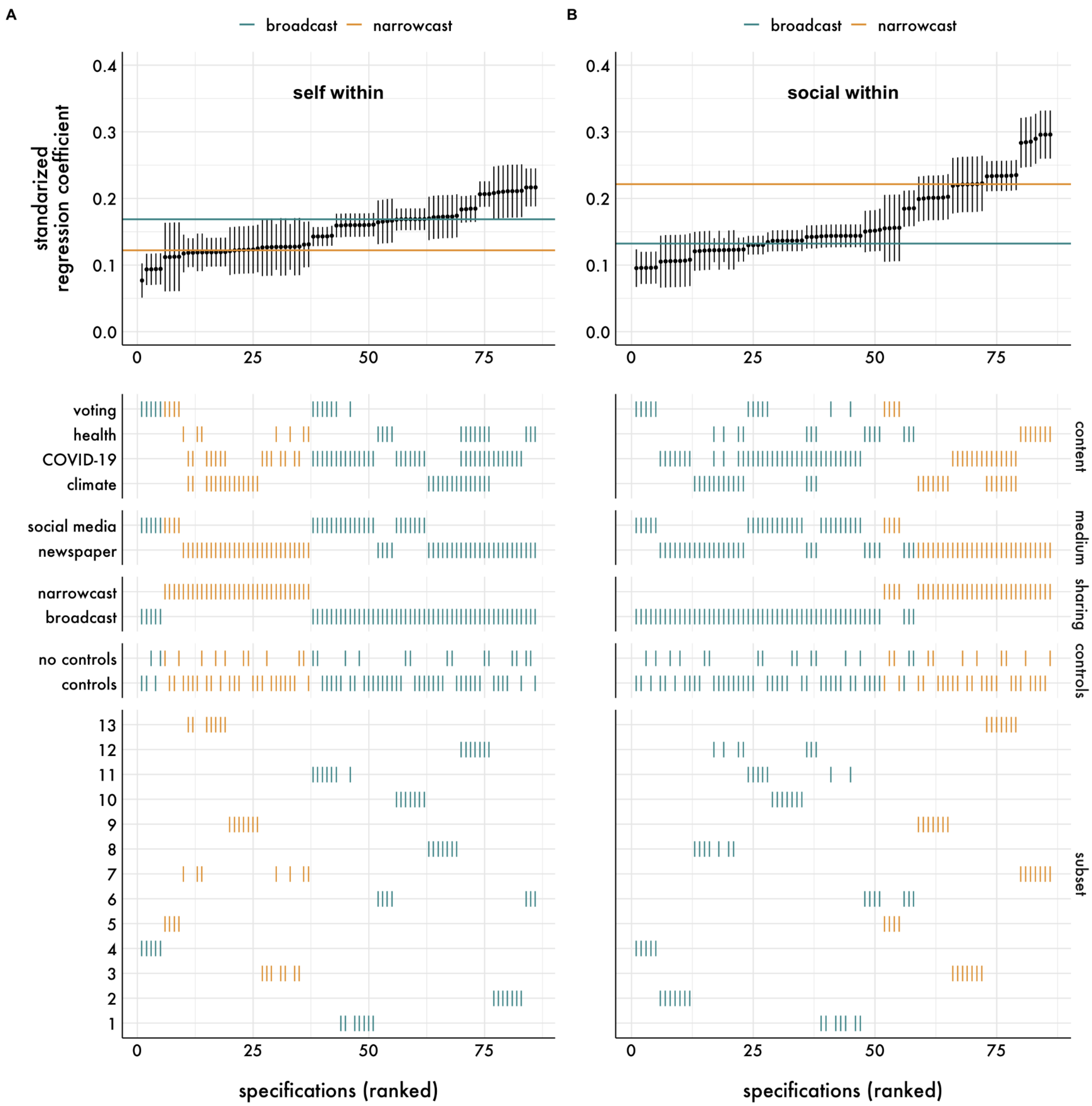

Figure S4. Specification curves for the within-person relevance variables reported in Figure 3C-D including an additional marker for which subset the model was estimated in. The subsets are described in Table S3.

Table S4

Specification curve descriptives statistics by sharing type and message medium

Sharing type

Parameter	Grouping variable	Median β	β Range	Positive & significant	Negative & significant
Self between	Broadcast	0.43	0.22, 0.74	100.00%	0.00%
	Narrowcast	0.48	0.24, 0.53	100.00%	0.00%
Self within	Broadcast	0.17	0.08, 0.22	100.00%	0.00%
	Narrowcast	0.12	0.11, 0.13	100.00%	0.00%
Social between	Broadcast	0.12	-0.08, 0.24	55.56%	0.00%
	Narrowcast	0.13	0.11, 0.22	78.12%	0.00%
Social within	Broadcast	0.13	0.10, 0.19	100.00%	0.00%
	Narrowcast	0.22	0.16, 0.30	100.00%	0.00%

Message medium

Parameter	Grouping variable	Median β	β Range	Positive & significant	Negative & significant
Self between	Newspaper	0.50	0.42, 0.74	100.00%	0.00%
	Social media	0.31	0.22, 0.36	100.00%	0.00%
Self within	Newspaper	0.15	0.12, 0.22	100.00%	0.00%
	Social media	0.16	0.08, 0.17	100.00%	0.00%
Social between	Newspaper	0.12	-0.08, 0.20	44.64%	0.00%
	Social media	0.18	0.15, 0.24	100.00%	0.00%
Social within	Newspaper	0.19	0.11, 0.30	100.00%	0.00%
	Social media	0.14	0.10, 0.16	100.00%	0.00%

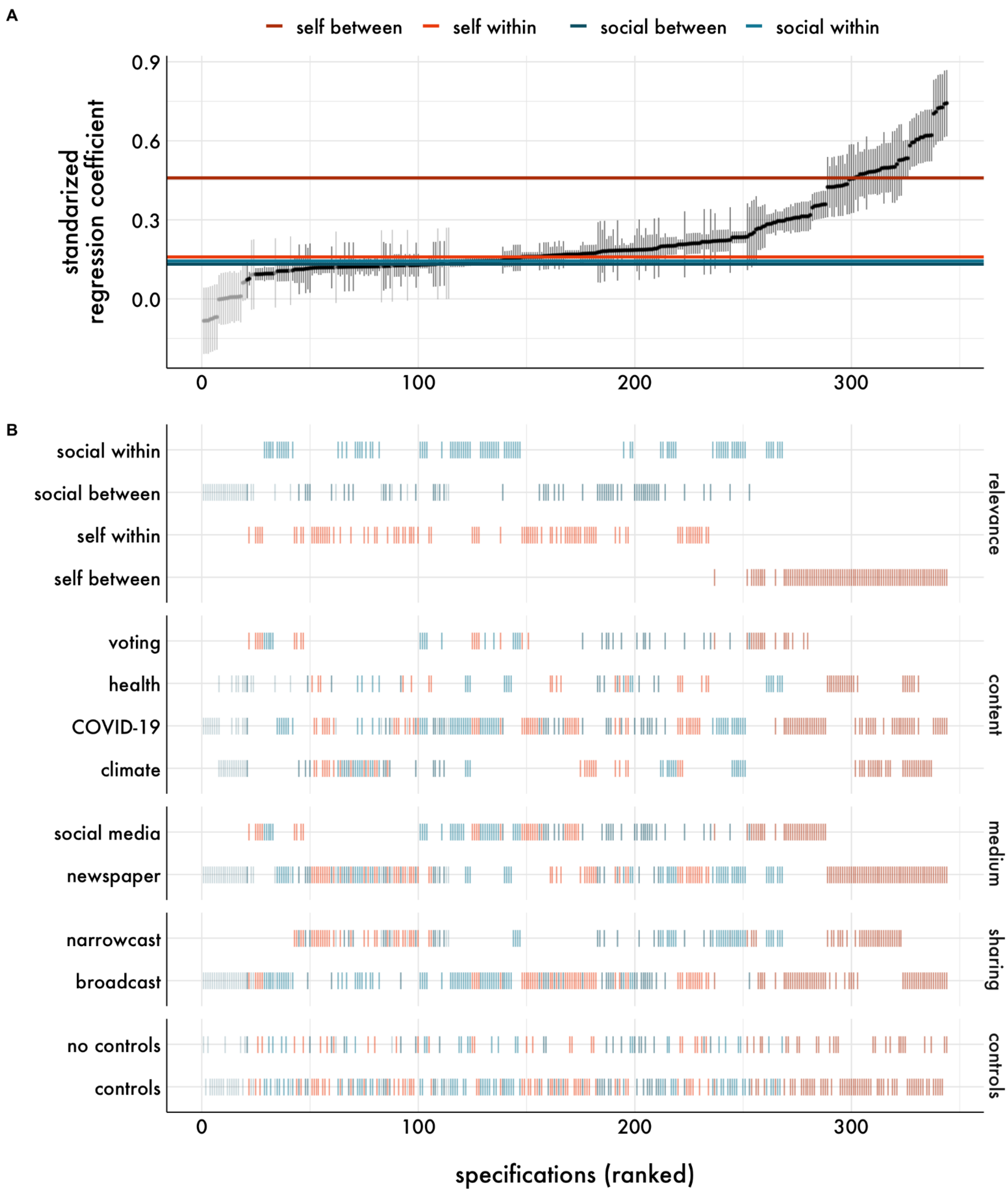

Figure S5. Specification curve visualizing the relationship between self and social relevance and sharing intentions across analytic decisions and subsets of the data. (A) The top panel depicts the relationship between the relevance variables and sharing intentions. Each dot represents the standardized 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. (B) The bottom panel shows the relevance variables and analytic decisions that were included in each model specification. Model specifications are colored based on the relevance variable; models for which the regression coefficient of interest was statistically significant at $p < 0.05$ are visualized are opaque, whereas coefficients $p > 0.05$ are partially opaque. Content = content type; medium = message medium; type = sharing type; controls = inclusion of demographic covariates.

Results from analyses estimated separately for each study

For completeness and to be consistent with our preregistered analysis plans for Studies 5 and 6, we also report the results for each study separately. As in the mega-analysis reported in the main manuscript, we investigated the relationships between message self and social relevance and broadcast sharing intentions using multilevel modeling. 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. Each of the “between-person” variables were level 2 predictors created by averaging across message self or social relevance ratings to create a single average per person that was then grand-mean centered and standardized across people.

For each study, we estimated three multilevel models regressing message sharing intentions on 1) within- and between-person self-relevance, 2) within- and between-person social relevance, and 3) within- and between-person self-relevance, and within- and between-person social relevance. The first and second models estimate the relationship between sharing intentions and self and social relevance separately, whereas the third model estimates each variables’ unique association with sharing intentions after adjusting for the others. In all models, intercepts and within-person relevance variables were allowed to vary randomly across people and intercepts could vary across messages. This was the least constrained random effects structure that converged across studies. All models were estimated using the *lme4* (Version 1.1-26; Bates et al., 2015) and *lmerTest* (Version 3.1-3; Kuznetsova, Brockhoff, & Chris-tensen, 2017) for significance testing in R (Version 3.6.3; R Core Team, 2020).

For the studies that included broad- and narrowcasting, we examined potential differences between broadcast and narrowcast sharing intentions by estimating a fourth model that included sharing type (broadcast or narrowcast) as a moderator of the relationship between self or social relevance and sharing intentions. In these models, intercepts and within-person relevance variables were allowed to vary randomly across people and messages, which was the least constrained random effects structure that converged across studies.

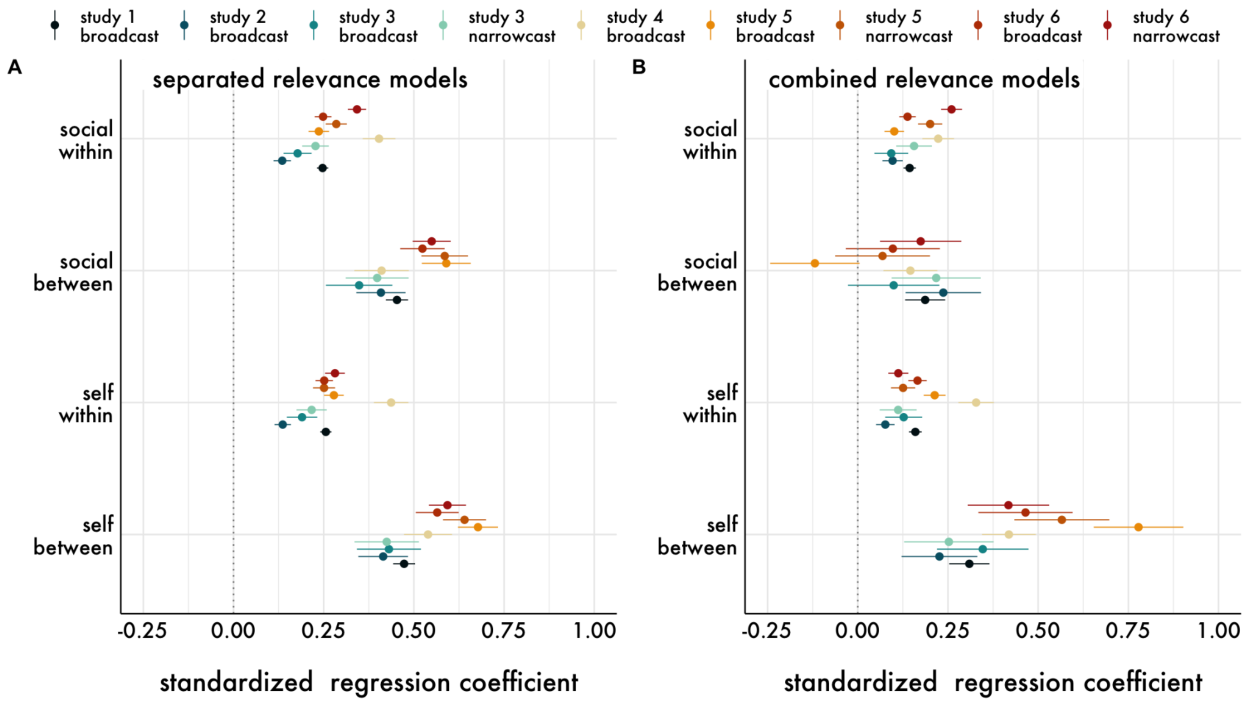

Figure S6. Standardized regression coefficients from (A) the models run separately including either the self-relevance or social relevance variables only, and (B) the models including the self and social relevance variables within the same model. "Within" parameters refer to the person-centered level 1 predictors, whereas "between" parameters refer to grand-mean centered level 2 predictors. Error bars around the point estimates are 95% confidence intervals.

First, we estimated the association between each relevance variable and sharing intention separately (Figure S6A; Tables S5-6). In all studies, within- and between-person self and social relevance were positively related to broad- and narrowcast sharing intentions, and the magnitude ranged from small to large effects.

Table S5

Results from the self-relevance multilevel models

Model	Parameter	β [95% CI]	*df*	*t*	*p*
Study 1 broadcast	Self between	0.47 [0.44, 0.50]	2145.50	30.47	< .001
	Self within	0.26 [0.24, 0.27]	1181.80	32.32	< .001
Study 2 broadcast	Self between	0.41 [0.35, 0.48]	555.65	11.81	< .001
	Self within	0.14 [0.11, 0.16]	265.79	11.74	< .001
Study 3 broadcast	Self between	0.43 [0.34, 0.52]	247.14	9.51	< .001
	Self within	0.19 [0.15, 0.23]	158.23	8.82	< .001
Study 3 narrowcast	Self between	0.42 [0.34, 0.51]	249.16	9.32	< .001
	Self within	0.22 [0.17, 0.26]	161.08	10.14	< .001
Study 4 broadcast	Self between	0.54 [0.47, 0.61]	142.31	15.88	< .001
	Self within	0.44 [0.39, 0.48]	121.19	17.93	< .001
Study 5 broadcast	Self between	0.68 [0.62, 0.73]	324.22	23.96	< .001
	Self within	0.28 [0.25, 0.31]	245.44	19.97	< .001
Study 5 narrowcast	Self between	0.64 [0.58, 0.70]	317.64	21.03	< .001
	Self within	0.25 [0.22, 0.28]	229.36	16.06	< .001
Study 6 broadcast	Self between	0.56 [0.51, 0.62]	405.99	18.60	< .001
	Self within	0.25 [0.23, 0.28]	334.94	20.35	< .001
Study 6 narrowcast	Self between	0.59 [0.54, 0.64]	398.73	22.62	< .001
	Self within	0.28 [0.25, 0.31]	328.95	20.12	< .001

Note. "Within" parameters refer to the person-centered level 1 predictors, whereas "between" parameters refer to grand-mean centered level 2 predictors. Coefficients are in standardized units. Degrees of freedom (*df*) were calculated using the Satterthwaite approximation.

Table S6

Results from the social relevance multilevel models

Model	Parameter	β [95% CI]	*df*	*t*	*p*
Study 1 broadcast	Social between	0.45 [0.42, 0.48]	2133.49	28.84	< .001
	Social within	0.25 [0.23, 0.26]	967.20	30.88	< .001
Study 2 broadcast	Social between	0.41 [0.34, 0.48]	548.93	11.74	< .001
	Social within	0.14 [0.11, 0.16]	272.42	10.95	< .001
Study 3 broadcast	Social between	0.35 [0.26, 0.44]	239.36	7.41	< .001
	Social within	0.18 [0.14, 0.22]	128.06	8.95	< .001
Study 3 narrowcast	Social between	0.40 [0.31, 0.49]	234.77	8.95	< .001
	Social within	0.23 [0.19, 0.26]	111.96	12.07	< .001
Study 4 broadcast	Social between	0.41 [0.33, 0.49]	139.34	10.66	< .001
	Social within	0.40 [0.36, 0.45]	103.95	17.47	< .001
Study 5 broadcast	Social between	0.59 [0.52, 0.66]	316.18	17.05	< .001
	Social within	0.24 [0.21, 0.26]	224.97	16.29	< .001
Study 5 narrowcast	Social between	0.59 [0.52, 0.65]	317.74	17.76	< .001
	Social within	0.28 [0.26, 0.31]	225.47	19.10	< .001
Study 6 broadcast	Social between	0.52 [0.46, 0.59]	402.78	16.68	< .001
	Social within	0.25 [0.22, 0.27]	303.88	20.92	< .001
Study 6 narrowcast	Social between	0.55 [0.50, 0.60]	401.49	20.42	< .001
	Social within	0.34 [0.32, 0.37]	287.96	26.55	< .001

Note. “Within” parameters refer to the person-centered level 1 predictors, whereas “between” parameters refer to grand-mean centered level 2 predictors. Coefficients are in standardized units. Degrees of freedom (*df*) were calculated using the Satterthwaite approximation.

Next, we tested whether self and social relevance accounted for unique variance when estimated within the same model, meaning that parameter estimates reflect the relationship after adjusting for the other variables in the model (Figure S6B; Table S7). All relationships between within- and between-person self and social relevance and sharing intentions were positive except in Study 5. In this study, between-person social relevance was negatively related to broadcast sharing intentions when adjusting for the other relevance variables in the model. In addition, this relationship did not differ significantly from zero in Studies 3 and 6. Together, this indicates that there is less consistency in the magnitude and direction of this relationship (compared to the other relevance variables) across studies.

Table S7
Results from the combined/ adjusted multilevel models

Model	Parameter	β [95% CI]	*df*	*t*	*p*
Study 1 broadcast	Self between	0.31 [0.25, 0.37]	2097.70	10.85	< .001
	Self within	0.16 [0.14, 0.18]	833.22	17.79	< .001
	Social between	0.19 [0.13, 0.24]	2073.58	6.59	< .001
	Social within	0.14 [0.13, 0.16]	781.23	16.49	< .001
Study 2 broadcast	Self between	0.23 [0.12, 0.33]	548.60	4.23	< .001
	Self within	0.08 [0.05, 0.10]	182.45	5.83	< .001
	Social between	0.24 [0.13, 0.34]	538.39	4.45	< .001
	Social within	0.10 [0.07, 0.12]	258.92	6.72	< .001
Study 3 broadcast	Self between	0.35 [0.22, 0.47]	246.17	5.35	< .001
	Self within	0.13 [0.08, 0.18]	115.16	4.86	< .001
	Social between	0.10 [-0.03, 0.23]	242.43	1.54	.130
	Social within	0.09 [0.05, 0.14]	128.47	3.88	< .001
Study 3 narrowcast	Self between	0.25 [0.13, 0.38]	252.18	3.99	< .001
	Self within	0.11 [0.06, 0.16]	91.050	4.28	< .001
	Social between	0.22 [0.09, 0.34]	245.30	3.45	< .001
	Social within	0.16 [0.11, 0.21]	109.51	6.18	< .001
Study 4 broadcast	Self between	0.42 [0.34, 0.49]	134.43	11.03	< .001
	Self within	0.33 [0.28, 0.38]	120.99	13.08	< .001
	Social between	0.15 [0.07, 0.22]	136.50	3.83	< .001
	Social within	0.22 [0.18, 0.27]	130.95	9.96	< .001
Study 5 broadcast	Self between	0.78 [0.65, 0.90]	322.02	12.28	< .001
	Self within	0.21 [0.18, 0.24]	220.10	13.76	< .001
	Social between	-0.12 [-0.24, 0.00]	319.53	1.88	.060
	Social within	0.10 [0.07, 0.13]	199.76	7.33	< .001
Study 5 narrowcast	Self between	0.57 [0.43, 0.70]	316.41	8.42	< .001
	Self within	0.13 [0.09, 0.16]	240.21	7.33	< .001
	Social between	0.07 [-0.06, 0.20]	316.03	1.02	.310
	Social within	0.20 [0.17, 0.23]	235.61	11.72	< .001
Study 6 broadcast	Self between	0.46 [0.33, 0.60]	376.82	6.97	< .001
	Self within	0.17 [0.14, 0.19]	316.63	12.71	< .001
	Social between	0.10 [-0.03, 0.23]	374.09	1.46	.140
	Social within	0.14 [0.12, 0.16]	250.99	11.81	< .001
Study 6 narrowcast	Self between	0.42 [0.30, 0.53]	380.44	7.25	< .001
	Self within	0.11 [0.08, 0.14]	279.68	7.92	< .001
	Social between	0.17 [0.06, 0.29]	378.34	3.03	< .001
	Social within	0.26 [0.23, 0.29]	281.19	17.57	< .001

Note. "Within" parameters refer to the person-centered level 1 predictors, whereas "between" parameters refer to grand-mean centered level 2 predictors. Coefficients are in standardized units. Degrees of freedom (*df*) were calculated using the Satterthwaite approximation.

Finally, for Studies 3, 5, and 6, we tested whether the relationships differed as a function of sharing type and directly compared broad- and narrowcast sharing intentions. Overall, the relationship between social relevance within- and between-person tended to be more strongly related to sharing intentions when narrowcasting than when broadcasting, whereas self-relevance tended to be more weakly related to sharing intentions when narrowcasting than when broadcasting (Table S8).

Table S8

Results from the sharing type interaction models

Model	Parameter	β [95% CI]	*df*	*t*	*p*
Study 3	Sharing type	-0.00 [-0.04, 0.04]	1987.51	-0.08	.940
	Social between	0.11 [-0.01, 0.23]	281.29	1.74	.080
	Social within	0.10 [0.05, 0.15]	248.94	3.64	< .001
	Self between	0.34 [0.22, 0.46]	284.52	5.60	< .001
	Self within	0.13 [0.07, 0.18]	180.74	4.48	< .001
	Social between x Sharing type	0.10 [0.03, 0.16]	1926.52	3.04	< .001
	Social within x Sharing type	0.05 [-0.01, 0.11]	1927.26	1.54	.120
	Self between x Sharing type	-0.08 [-0.14, -0.01]	1926.33	-2.40	.020
	Self within x Sharing type	-0.01 [-0.07, 0.05]	1938.52	-0.29	.770
Study 5	Sharing type	-0.00 [-0.02, 0.02]	5741.47	0.00	1.000
	Social between	-0.14 [-0.27, -0.02]	346.17	-2.27	.020
	Social within	0.10 [0.06, 0.13]	372.59	6.17	< .001
	Self between	0.81 [0.68, 0.93]	347.20	12.78	< .001
	Self within	0.21 [0.18, 0.24]	408.53	12.96	< .001
	Social between x Sharing type	0.23 [0.18, 0.28]	5436.83	9.12	< .001
	Social within x Sharing type	0.11 [0.08, 0.14]	5436.83	6.98	< .001
	Self between x Sharing type	-0.26 [-0.31, -0.21]	5436.83	-10.14	< .001
	Self within x Sharing type	-0.09 [-0.12, -0.06]	5436.83	-5.58	< .001
Study 6	Sharing type	-0.00 [-0.02, 0.02]	7181.45	0.00	1.000
	Social between	0.13 [0.01, 0.25]	418.42	2.14	.030
	Social within	0.12 [0.10, 0.15]	509.14	9.41	< .001
	Self between	0.45 [0.33, 0.57]	419.87	7.39	< .001
	Self within	0.16 [0.14, 0.19]	543.19	12.43	< .001
	Social between x Sharing type	0.04 [-0.01, 0.08]	6801.62	1.46	.140
	Social within x Sharing type	0.14 [0.11, 0.17]	6801.63	9.93	< .001
	Self between x Sharing type	-0.02 [-0.07, 0.03]	6801.62	-0.92	.360
	Self within x Sharing type	-0.06 [-0.09, -0.03]	6801.72	-4.03	< .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.