The science of sharing and the sharing of science

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Why do members of the public share some scientific findings and not others? What can scientists do to increase the chances that their findings will be shared widely among nonscientists? To address these questions, we integrate past research on the psychological drivers of interpersonal communication with a study examining the sharing of hundreds of recent scientific discoveries. Our findings offer insights into (*i*) how attributes of a discovery and the way it is described impact sharing, (*ii*) who generates discoveries that are likely to be shared, and (*iii*) which types of people are most likely to share scientific discoveries. The results described here, combined with a review of recent research on interpersonal communication, suggest how scientists can frame their work to increase its dissemination. They also provide insights about which audiences may be the best targets for the diffusion of scientific content.

word of mouth | social transmission | science communication | framing

Some scientific discoveries are shared widely outside the scientific community. Nonscientists describe them to friends over coffee and email them to colleagues at work. Articles about these discoveries might even appear among the most emailed stories on major news websites. Other scientific findings, however, are rarely shared, even if they receive media attention. Why? What leads nonscientists to transmit some discoveries more than others, and how can scientists use this knowledge to describe their findings in more compelling ways?

These questions have received relatively little attention in the literature, but they are important to both scientists and society at large. First, knowledge propagation increases impact. Scientific discoveries (e.g., vaccines for shingles or the finding that defaulting employees into 401k plans dramatically increases savings rates) can improve people's health and well-being. However, for these discoveries to change behavior or policy, they have to diffusefrom academic journals to the population at large. Wide sharing of a discovery among nonscientists is one way that such diffusion can take place. Second, scientific funding depends in part on public interest and support. Widespread sharing increases the chances that streams of research will be perceived as important and worthy of taxpayer support.

This paper addresses several important, open questions about what leads scientific discoveries to be shared. Communication research has examined what news outlets value (1, 2) and what news captures public attention (3), but we focus on what nonscientists are most likely to share.

We examine both the science of sharing and the sharing of science. First, we review and synthesize psychological research on what types of content are most likely to be shared. Second, we augment this discussion with data on the sharing of scientific discoveries. We consider both (*i*) what types of discoveries are likely to be shared and (*ii*) ways that scientists can more effectively frame or describe their work to increase its transmissibility. Our data analyses also suggest what types of disciplines and researchers tend to produce research that nonscientists will share. Finally, we explore whether certain types of people are more likely to share scientific discoveries, identifying groups that might be particularly receptive to scientific outreach.

To examine the sharing of science, we contacted scientists who had recently published an article in a leading scientific journal and asked them to summarize their findings for a lay audience (see *Methods* for details). More than 800 scientists from more than 400 institutions replied. More than 7,000 nonscientists were then exposed to a randomly selected scientific summary and rated their likelihood of sharing this finding. They also rated the summary on a number of other dimensions. These data allow us to examine a variety of questions about people's willingness to share science and to test whether prior findings about the sharing of other content (e.g., news articles, products, online reviews) also apply to the sharing of science. Importantly, often in our dataset, multiple coauthors of the same paper appear and describe the same discovery in their own words. Analyzing these coauthor summaries allows us to disentangle whether the topic of a scientific discovery itself, or the way that it is described, drives its transmissibility.

Content Effects: How Do Content Characteristics Affect Sharing?

Although not focused on science, past research has explored the psychological drivers of sharing content ranging from news articles to new products (4–14). We briefly summarize this work and use our data on scientists' discoveries to examine whether insights from other contexts also apply to the sharing of science.

Self-Enhancement. One reason people share news and information is to self-enhance or generate desired impressions. Just like the music people listen to, or the brands they buy, what they talk about and share affects how others see them. Consequently, people are more likely to share things that make them look good or enable them to signal desired identities (15–20).

The desire to share content that is self-enhancing manifests itself in a number of ways. First, people are more likely to share surprising, interesting, or otherwise entertaining content. Interesting products (e.g., night vision goggles) receive more online word of mouth than mundane products (e.g., soap) (12). Similarly, more interesting and surprising news articles are more likely to make the *New York Times'* most emailed list (4); more interesting and surprising urban legends are more likely to spread (6); and more interesting advertisements receive more views.

Second, people are more likely to share useful information, in part because doing so makes them look smart and in-the-know. If someone tells you about a medication that will quickly cure your cold or a website for last-minute travel deals, it demonstrates the sharer's knowledge and expertise. Consistent with this perspective, more useful news stories (4, 6) and marketing messages (21) are more likely to be widely shared.

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Third, positive content is more likely to be shared than negative content. People prefer to make others feel good rather than bad. Further, people prefer to spend time with others who are upbeat and positive (22) and what people share is a reflection of who they are. Consistent with this, people are more likely to share positive *New York Times* articles (4) and positive advertisements (23).

Theoretically, self-enhancement motives should also apply to the sharing of science. The more positively sharing scientific information reflects on the sender, the more likely people should be to pass it along. People should be more likely to transmit research findings that are interesting, surprising, useful, and positive. These findings do not mean scientific discoveries should be dumbed down, but rather that effective diffusion of discoveries requires considering what people find interesting, useful, or positive and framing discoveries to take advantage of that knowledge. When writing a press release describing a process for producing a new type of crystal, for example, it would be wise to emphasize how this crystal can be used (e.g., for efficiently converting light into electricity) and why this breakthrough is exciting (e.g., this could help produce clean energy), surprising, and new (e.g., no such uses had been proposed previously for a similar class of materials). Describing findings in a way that generates positive emotion should also boost transmission.

Social Bonding. Another reason people share news and information is to deepen connections with others (7). Some authors (24, 25) have suggested that language evolved to allow humans to reinforce bonds and keep track of a large set of people in their social circle. Whether or not this is the case, it is clear that sharing reinforces shared views and strengthens connections.

Sharing emotional content is one way to enhance social bonds (26). It produces a shared experience for the transmitter and recipient and increases cohesiveness (27). For example, if something makes someone angry, sharing it with someone else may make that person angry too, and the shared emotional experience will draw both members of the pair closer together.

Consistent with this notion, past research has shown that more emotional content is more likely to be shared (7). Movies, news, emails, and social anecdotes are all more likely to be shared if they are higher in emotional intensity (4, 21, 28, 29). Along these lines, more emotional scientific discoveries, or scientific discoveries that are framed in a more emotional manner, should be more likely to be shared.

Testing Whether These Factors Impact the Sharing of Science. To investigate whether these factors shape the sharing of science, we collected data from scientists and members of the public (*Methods*). We rely on ordinary least-squares regressions to predict survey respondents' willingness to share a given scientist's summary of a recent discovery, controlling for its' author's discipline, demographic characteristics, and the journal where the findings were published. Note that throughout this paper, each analysis is conducted using two different primary regression specifications (see *Methods* for details). To reference *P* values associated both primary regression specifications, we will refer to "both *P*s."

In the results presented in Table 1, models 3 and 4 show that more positive (both $P\text{s} < 0.05$), emotional (both $P\text{s} < 0.001$), interesting (both $P\text{s} < 0.001$), and useful scientific discoveries (both $P\text{s} < 0.001$), as well as discoveries that reflect more positively on the sender (both $P\text{s} < 0.01$), are all more likely to be shared. Although the strongest predictor of willingness to share is how interesting a discovery is perceived to be ($\beta_{\text{interesting}} = 0.40$ in Table 1, model 4),* the second strongest predictor is a discovery's emotionality ($\beta_{\text{emotionality}} = 0.27$ in Table 1, model 4). Even though science is based on factual information, this finding highlights the importance of communicating findings in a way that arouses emotion.

Framing a Discovery to Increase Transmissibility. Our data suggest what kinds of scientific discoveries are likely to be shared, but they also allow us to examine what an author can do, given a fixed topic of inquiry, to communicate her findings in a way that will increase diffusion. To address this question, we examine different summaries (written by academic coauthors) of the same scientific discoveries to see how framing the same finding differently impacts its transmission likelihood.

We take advantage of the fact that many ($n = 231$) of the papers in our dataset were described by multiple coauthors. Adding fixed effects to our regression model to control for the contents of a given scientific discovery allows us to control for the finding itself. We can then examine how different characteristics of the finding's description relate to its likelihood of being shared. We take this empirical approach in Table 1, models 5–8. Table 2 presents examples of how distinctly the same scientific discoveries are described by different coauthors in our dataset.

Our results are again consistent with prior research on sharing. Scientific discoveries that are framed in more useful, interesting, and emotional ways are more likely to be shared (models 7 and 8 in Table 1 and Fig. 1). We even find that summaries containing more emotional words are more likely to be shared (adding LIWC Emotionality as a predictor to Table 1, model 5, and controlling, as usual, for word count and LIWC positivity, we see $P_{\text{LIWC\_emotionality}} < 0.05$; adding these predictors to Table 1, model 6, we see $P_{\text{LIWC\_emotionality}} = 0.06$). In one specification, we also observe increased transmissibility when transmission reflects more positively on the sender (Table 1, model 8; $P < 0.001$) and marginal benefits associated with more positive summaries (Table 1, model 8; $P < 0.10$). Note that the effect sizes depicted in Fig. 1 are quite large, especially considering that we are identifying off of the impact of differences in the way coauthors frame the same scientific finding.

These findings suggest a number of things scientists can do to increase the diffusion of their work. When describing one's work to a lay audience, framing findings in a way that (*i*) arouses emotion or makes the work seem more (*ii*) useful or (*iii*) interesting should increase the likelihood they are shared.

We next explore how author characteristics relate to sharing.

Creator Effects: Who Generates Sharable Discoveries?

Author Demographics. Women must overcome many hurdles to advance scientific research careers (30–33). However, when it comes to transmission, a massive study of which *New York Times* articles are highly shared found that female first authors produce content that is more widely transmitted, even after controlling for an article's topic (4). Might women select more sharable ideas or communicate ideas in a way that makes them more likely to be shared?

Table 1 (models 1 and 2) provides preliminary insights into whether female authors produce particularly shareable content. Results indicate that female authors write summaries that are 5% more likely to be shared (both $P\text{s} < 0.05$).†

Further analyses suggest that these differences are driven by characteristics of the summaries these authors produced. When we add content characteristics (i.e., the extent to which content is interesting, useful, comprehensible, emotional, and positive, and whether it reflects positively on the person transmitting it; Table 1, models 3 and 4) to the model, we find that the effects of author demographics on sharing are almost fully accounted for. These findings suggest that the summaries written by female authors differ

*All references to effect sizes throughout this paper (and in figures) rely on models including one observation per rater ($n = 7{,}478$) in which SEs are clustered by article. Effect sizes from models that instead include one observation per article ($n = 845$) can be calculated from Table 1 and are nearly identical.

†Although not predicted ex ante, we also observe that summaries penned by Asian authors are 12% less likely to be shared than those by Caucasian authors (both $P\text{s} < 0.01$).

Table 1. Ordinary least-squares regressions to predict a scientific summary's rated likelihood (models 1, 3, 5, and 7) or average rated likelihood (models 2, 4, 6, and 8) of being shared

	Comparison between scientific discoveries				Comparison within scientific discoveries			
Predictor variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Author characteristics								
Male	−0.165**	−0.166**	−0.040	−0.031	−0.065	−0.071	−0.020	−0.012
	(0.067)	(0.067)	(0.040)	(0.042)	(0.102)	(0.091)	(0.064)	(0.060)
Caucasian	−0.033	−0.046	−0.036	−0.042	0.089	0.066	0.006	−0.007
	(0.093)	(0.094)	(0.051)	(0.051)	(0.157)	(0.140)	(0.096)	(0.091)
Asian	−0.384****	−0.391****	−0.119*	−0.106	−0.127	−0.151	0.002	−0.019
	(0.110)	(0.111)	(0.063)	(0.064)	(0.191)	(0.168)	(0.114)	(0.110)
Age	−0.001	−0.001	−0.001	−0.001	−0.005	−0.005	−0.004*	−0.004
	(0.002)	(0.002)	(0.001)	(0.001)	(0.004)	(0.003)	(0.002)	(0.002)
Professor	0.009	0.001	0.044	0.043	−0.088	−0.005	0.003	0.001
	(0.062)	0.063	(0.035)	(0.036)	(0.103)	(0.003)	(0.061)	(0.060)
Rater characteristics								
Male	0.174****	—	0.077**	—	0.184****	—	0.083**	—
	(0.042)	—	(0.031)	—	(0.042)	—	(0.033)	—
Caucasian	−0.167***	—	−0.009	—	−0.160***	—	−0.016	—
	(0.057)	—	(0.044)	—	(0.059)	—	(0.045)	—
Asian	0.146*	—	0.078	—	0.187**	—	0.089	—
	(0.079)	—	(0.059)	—	(0.083)	—	(0.061)	—
Age	−0.002	—	−0.004***	—	−0.002	—	−0.004**	—
	(0.002)	—	(0.001)	—	(0.002)	—	(0.002)	—
Summary characteristics								
LIWC positivity	—	—	0.400**	0.433**	—	—	0.460*	0.531
	—	—	(0.165)	(0.174)	—	—	(0.249)	(0.337)
Wordcount × 10	—	—	−0.005	−0.005	—	—	−0.003	−0.002
	—	—	(0.003)	(0.003)	—	—	(0.005)	(0.005)
Interesting	—	—	0.374****	0.400****	—	—	0.367****	0.335****
	—	—	(0.015)	(0.037)	—	—	(0.016)	(0.061)
Usefulness	—	—	0.154****	0.152****	—	—	0.159****	0.267****
	—	—	(0.014)	(0.036)	—	—	(0.015)	(0.059)
Reflects positively	—	—	0.158****	0.122***	—	—	0.161****	0.091
	—	—	(0.017)	(0.045)	—	—	(0.018)	(0.067)
Emotionality	—	—	0.253****	0.274****	—	—	0.247****	0.201****
	—	—	(0.015)	(0.037)	—	—	(0.016)	(0.057)
Comprehensibility	—	—	0.009	0.017	—	—	0.004	0.003
	—	—	(0.012)	(0.029)	—	—	(0.013)	(0.046)
Additional controls: Fixed effects for author's field, fixed effects for journal,† rater age missing (indicator),‡ fixed effects for rater participant pool‡								
Article fixed effects	No	No	No	No	Yes	Yes	Yes	Yes
Clustering by	Article	None	Article	None	Article	None	Article	None
Analytic weights	None	No. of Raters	None	No. of Raters	None	No. of Raters	None	No. of Raters
No. of observations	7,478	845	7,478	845	7,478	845	7,478	845
No of unique summaries	845	845	845	845	845	845	845	845
No. of unique articles	474	474	474	474	474	474	474	474
R^2	0.05	0.19	0.51	0.72	0.15	0.73	0.54	0.89

Models 1–4 examine differences in what types of summaries are most likely to be shared. Models 5–8 include article fixed effects to examine differences in ratings of summaries of the same scientific discovery. SEs are shown in parentheses.

$*P < 0.10$; $**P < 0.05$; $***P < 0.01$; $****P < 0.001$.

†These controls cannot be included in models with article fixed effects (models 5–8).

‡These controls cannot be included in models that have just one observation per article (models 2, 4, 6, and 8).

along a subset of these dimensions in a way that explains sharing likelihood. Analyzing this possibility variable by variable while controlling for an author's discipline with fixed effects shows that female authors write more comprehensible (both Ps < 0.01), useful (both Ps < 0.001), and interesting (both Ps < 0.01) scientific summaries, all of which independently mediate the effect of sex on sharing (Ps $<$ 0.05 from all bootstrapped mediation tests with 1,000 resamples).

These findings are intriguing, but it remains unclear whether they are driven by (*i*) differences in how people communicate ideas or (*ii*) differences in topic selection. Women may be better at communicating ideas in ways that make them transmissible or they may select research topics that are more likely to be shared.

To distinguish between these two possibilities (communication skills vs. topic selection), we again take advantage of the fact that many of the papers in our dataset were described by multiple coauthors. We introduce fixed effects for a given scientific discovery (or article fixed effects) into our regression models, which, as described previously, allows us to identify what characteristics of different summaries drive sharing given the same scientific finding. As models 5 and 6 in Table 1 show, controlling for the underlying scientific finding that an author is describing eliminates any effect of an author's demographics on sharing. These findings indicate that the previously observed differences in transmission as a function of an author's sex are driven by topic selection

Table 2. Examples of summaries of the same article by different coauthors that differ on numerous dimensions

Sample article A			
Summary 1A		Summary 2A	
"More than 170 million people, 3% of the world's population, are infected with Hepatitis C virus. There is no vaccine and better therapies are needed to cure the infection. Despite many years of study, we still do not even know the detailed structure of this virus. In this paper, we describe new methods to obtain pure virus and show preliminary results for a low-resolution 3D structure. This should lead to better structures in the future and to a better understanding of this important virus."		"[We] used a series of methods, including electron cryomicroscopy and labeling to study the structure of human hepatitis C virus. Hepatitis C is an infectious disease, which when not treated can lead to cirrhosis of the liver, liver cancer and ultimately death. The work presented in this paper tries to shed light on the location of certain viral components on the outer shell or capsid of the virus, something that has remained elusive for years. Using labeling techniques, along with electron tomograph (similar to a CAT scan), [we] were able to, for the first time, point with much certainty, where certain regions of the virus are and how it looks."	
Avg. Likelihood of sharing:	4.6	Avg. Likelihood of Sharing:	2.8
LIWC Emotionality:	6.8%	LIWC Emotionality:	2.3%
LIWC Positivity:	4.1%	LIWC Positivity:	2.3%
Avg. Rating of interestingness:	5.3	Avg. Rating of interestingness:	3.8
Avg. Rating of Usefulness:	5.5	Avg. Rating of Usefulness:	4.2
Avg. Rating of Reflects Positively:	4.8	Avg. Rating of Reflects Positively:	3.8
Avg. Rating of Emotionality:	3.6	Avg. Rating of Emotionality:	2.3
Avg. Rating of Comprehensibility:	5.8	Avg. Rating of Comprehensibility:	4.0
Sample article B			
Summary 1B		Summary 2B	
"We produced a device that, although atomically thin, can strongly absorb light and convert it to electricity in a very efficient way. For every 100 photons of light, 30 are converted to electricity, which is a value comparable to the best solar cells in the market."		"We are trying to build new types of crystal by combining layers from different materials. We've previously shown that these can have many applications in digital and analog electronics. In this work we were able to turn light into electricity with a high conversion rate using our new structures made from graphene and tungsten disulfide, both atomically thin layered crystals."	
Avg. Likelihood of Sharing:	5.4	Avg. Likelihood of Sharing:	3.7
LIWC Emotionality:	18.9%	LIWC Emotionality:	0%
LIWC Positivity:	18.9%	LIWC Positivity:	0%
Avg. Rating of Interestingness:	5.6	Avg. Rating of Interestingness:	3.9
Avg. Rating of Usefulness:	6	Avg. Rating of Usefulness:	4.3
Avg. Rating of Reflects Positively:	5.4	Avg. Rating of Reflects Positively:	5.1
Avg. Rating of Emotionality:	4	Avg. Rating of Emotionality:	2.6
Avg. Rating of Comprehensibility:	5.6	Avg. Rating of Comprehensibility:	4.6
Sample article C			
Summary 1C		Summary 2C	
"The Circadian clock is tightly related to our health and a lot of biological process. We solved the 3-D structure of a very important protein complex in the mammalian circadian clock pathway. The structure will help us to understand how the circadian clock works and how the circadian clock could be regulated. Also, we could design some better drug to change the circadian clock period and better adjust the jetlag."		"With this research, we have been able to visualize at atomic level the interaction of the cryptochrome proteins with Fbxl3. We discovered that the FAD, a known intracellular metabolite, regulates the crypthochrome-Fbxl3 interaction, thus modulating the circadian clock. Our study opens an important door for the development of drugs that can control the circadian rhythms."	
Avg. Likelihood of Sharing:	4.5	Avg. Likelihood of Sharing:	1.6
LIWC Emotionality:	6.1%	LIWC Emotionality:	3.2%
LIWC Positivity:	6.1%	LIWC Positivity:	3.2%
Avg. Rating of Interestingness:	5.0	Avg. Rating of Interestingness:	1.6
Avg. Rating of Usefulness:	5.4	Avg. Rating of Usefulness:	1.8
Avg. Rating of Reflects Positively:	5.0	Avg. Rating of Reflects Positively:	4.2
Avg. Rating of Emotionality:	2.9	Avg. Rating of Emotionality:	1.2
Avg. Rating of Comprehensibility:	4.1	Avg. Rating of Comprehensibility:	1.6

rather than communication tendencies. Women do not communicate research in a way that makes it any more or less transmissible. However, even after controlling for their disciplinary affiliation (e.g., psychology), women work on research topics that nonscientists find more comprehensible, useful, and interesting. These differences in topic selection, in turn, drive differences in transmissibility as a function of author sex.

Author Discipline. We also examined whether nonscientists are more willing to share discoveries from certain disciplines. Fig. 2 summarizes differences in willingness to share across academic journals and author disciplines.

As Fig. 2*A* highlights, people report being more likely to share social science discoveries ($M = 3.55$) than general science discoveries [$M = 3.00$; $t(7{,}478) = -8.51$; $P < 0.001$]. Within the

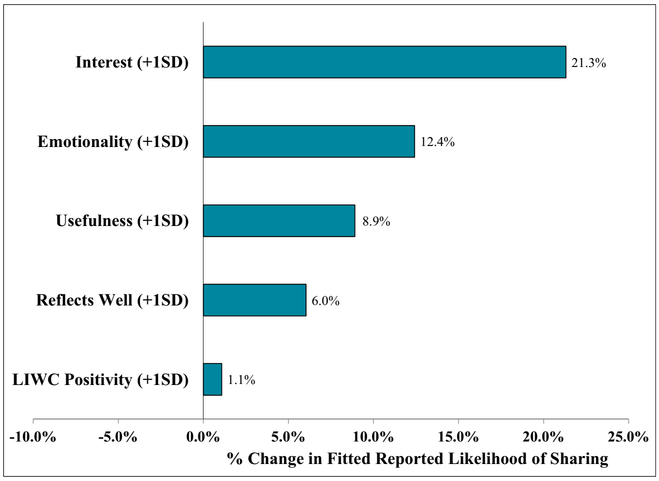

Fig. 1. Percentage change in fitted reported likelihood of sharing for a 1 SD increase above the mean in the value of a given summary characteristic (based on regression model 7 in Table 1).

social sciences, people report being most likely to share psychological discoveries [$M_{\text{psychology}} = 3.75$; $M_{\text{economics\_and\_sociology}} = 3.24$; $t(2{,}606) = 5.41$; $P < 0.001$] and less likely to share economic ($M = 3.25$) and sociological discoveries ($M = 3.23$), which are shared at similar rates [$t(1{,}009) = 0.17$; $P > 0.8$].

Analyzing authors' disciplinary affiliation(s) (e.g., business, math, and chemistry; including one observation per rating) provides a finer-grained picture of sharing by discipline (Fig. 2*B*). Notably, the differences in sharing between disciplines are significantly more substantial than would be expected by chance [$F(18{,}473) = 7.16$; $P < 0.0001$], which means that differences between disciplines are not simply due to random noise but are substantive. Articles by business academics, psychologists, and economists, for example, are more likely to be shared than articles by physicists, geneticists, and biochemists (for all of these nine paired comparisons, $P < 0.05$).

Why might the public be more willing to share business and psychology discoveries? One possibility is that discoveries referencing people (*Methods*) are more likely to be shared. Specifically, we find that a 1 SD (or 3 percentage point) increase in the percentage of words referencing people (e.g., adult, baby, or boy) is associated with a fitted 5% increase in raters' self-reported willingness to share a scientific summary (both Ps < 0.001).

Audience Effects: Are Certain Types of People More Likely to Share Scientific Discoveries?

Finally, we examine whether audiences with certain demographic characteristics are more willing to spread scientific discoveries. Note that our analyses are based on the assumption that different demographic groups interpret and use our survey response scales in the same way.[‡]

As models 1 and 5 in Table 1 show, men report a 6% higher willingness to share the same scientific discoveries than women (both Ps < 0.001), even after controlling for the field in which those discoveries were made and including fixed effects (in model 5) for the specific discovery. As models 3 and 7 reveal, these sex differences are largely driven by raters' assessments of how interesting, useful, emotional, and comprehensible an article is, as well as its likelihood of reflecting positively on them if they share (because once these additional predictors are added to models 1 and 5, sex effects are cut to about one third of their original magnitude). Specifically, men see the same scientific summaries as more comprehensible ($P < 0.001$), interesting ($P < 0.001$), and useful ($P < 0.05$), and the predictors' comprehensibility and interesting both independently mediate the effects of rater sex on sharing (Ps < 0.05 from both bootstrapped mediation tests with 1,000 resamples).

Furthermore, Caucasian respondents report a 5% lower willingness to share (models 1 and 5; both Ps < 0.05) than respondents who classified their race as Hispanic, black, and other, whereas Asian respondents report a 6% higher willingness to share in some specifications (models 1 and 5), again after controlling for the field in which a discovery was made.

Adding controls for content characteristics (models 3 and 7) eliminates these effects, suggesting that racial differences are driven by differences in perceptions of a scientific discovery's content. On average, Caucasians perceived the same summaries to be less comprehensible ($P < 0.001$), less emotion-inducing ($P < 0.001$), less likely to reflect positively on them if shared ($P < 0.001$), less useful ($P < 0.001$), and less interesting ($P < 0.01$). All of these correlated characteristics independently mediate the effects of Caucasian raters on sharing (Ps < 0.05 from all bootstrapped mediation tests with 1,000 resamples), but the primary sources of the effect appear to be how useful an article is perceived to be and how much emotion it induces. On the flip side, Asians perceived the same summaries to be more emotion-inducing ($P < 0.001$), more useful ($P < 0.001$), more likely to

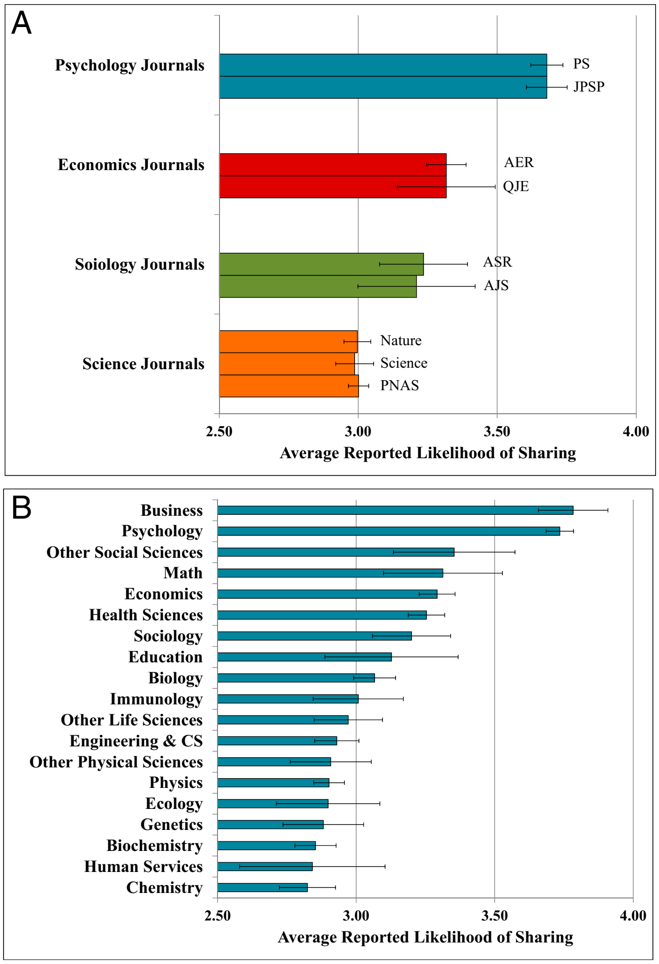

Fig. 2. (*A*) Average likelihood of sharing by discipline and journal. (*B*) Average likelihood of sharing by author's scientific field. Error bars depict 1 SE.

‡It is possible that instead, some groups tend to give higher ratings on response scales than others but are no more likely to actually share content. We will assume in our analyses that this is not the case but note that we cannot rule out this possibility.

reflect positively on them if shared ($P < 0.05$), and more interesting ($P < 0.05$). Emotionality and usefulness both independently mediate the effects of Asian raters on sharing (Ps < 0.05 from both bootstrapped mediation tests with 1,000 resamples). No effects of a rater's education on sharing were detected (all Ps > 0.10). Thus, different demographic groups may tend to perceive the same discovery differently, in turn driving their differential willingness to share.

Discussion

Nonscientists share some scientific discoveries more than others. Why? How can scientists increase the likelihood that their findings will be widely shared? We review past research and analyze data collected from scientists and members of the public to shed light on these questions, and our results fall into three main areas.

First, we explore what characteristics of scientific discoveries, and of how they are framed, impact sharing. Past research on persuasive communication suggests how messages can be crafted to increase their appeal, informativeness, trustworthiness, and persuasiveness (34–36). We contribute to this literature by demonstrating how crafting scientific summaries can increase another important outcome: transmissibility. Much past research on the science of sharing applies to the sharing of science, and we find that there are specific things scientists can do to encourage nonscientists to share their research. Framing research in a way that (*i*) evokes stronger emotion, (*ii*) increases perceived usefulness, (*iii*) draws greater interest, or (*iv*) is more positive should all bolster transmission.

Second, we examine who generates sharable discoveries, showing that female authors select topics that nonscientists report greater willingness to share. We also find that research by social scientists (particularly psychologists) is rated as particularly shareable, potentially because individuals are more willing to share research about people.

Future research might examine why women study topics that are more compelling to nonacademic audiences. A recent study suggests one possibility: women publish less often in one leading psychology journal, but their publications in that journal are more widely cited than men's publications (37). This finding suggests that women may be better at selecting impactful topics.

Third, we identify demographic groups (namely, men and minorities) with a particularly high willingness to pass along scientific discoveries, suggesting where scientists' communication efforts may be most efficiently targeted. It is interesting to note that members of the same demographic groups that produce science that raters report a lower likelihood of sharing (men and Asians, see (Table 1[†]) also report a higher likelihood of passing along a given scientific discovery. Might these demographic groups have different thresholds for what they find interesting? Might they find different types of scientific content more compelling? Future research seeking to uncover the source of these patterns might explore these questions.

In conclusion, although there is much more research to be done, there is a great deal scientists can do to increase the likelihood that their discoveries are shared. By understanding the science of sharing, we can increase the sharing of science.

Methods

Authors of Scientific Summaries. We recruited scientists who had authored a paper published in a leading science or social science journal between January 1 and June 15, 2013. Specifically, all 4,214 of the first eight[§] coauthors and sole authors of papers published during this period at *Science* (n = 1,785), *Nature* (n = 448), *The American Economic Review* (n = 318), *The Quarterly Journal of Economics* (n = 49), *The American Sociological Review* (n = 40), *The American Journal of Sociology* (n = 34), *Psychological Science* (n = 408), and *The Journal of Personality and Social Psychology* (n = 224) whose contact information was available online were invited to participate, as well as the first eight coauthors and all sole authors of papers published in the June 4, 2013 and June 11, 2013 issues of the *Proceedings of the National Academies of Sciences USA* (*PNAS*) (n = 908) whose contact information was available online.[¶] These authors received an email inviting them to complete a short survey about a specific paper they had published in one of the aforementioned journals in 2013 in exchange for a chance to

Table 3. Characteristics of the authors of scientific summaries

Characteristic	Mean	SD
Age	42.2	13.7
Number of Coauthors	8.4	13.6
Author order	3.9	5.6
	Percentage	
Male	75.4%	
Race		
Caucasian	76.6%	
Asian	15.6%	
Other	7.8%	
Hispanic	4.5%	
Black	0.4%	
Other	2.2%	
Academic position		
Full professor	27.6%	
Associate professor	9.2%	
Assistant professor	15.3%	
Postdoctoral researcher	18.9%	
Lecturer	2.0%	
PhD student	13.0%	
Other	13.1%	
Primary research field		
Biochemistry	7.1%	
Biology	6.0%	
Business	3.3%	
Chemistry	3.2%	
Ecology	0.8%	
Economics	11.2%	
Education	0.6%	
Engineering and computer science	7.0%	
Genetics	1.7%	
Health sciences	11.0%	
Human services	0.4%	
Immunology	1.3%	
Math	0.9%	
Other life sciences	2.8%	
Other natural and physical sciences	2.0%	
Other social sciences	0.8%	
Physics	13.8%	
Psychology	14.3%	
Sociology	2.1%	
Journal		
Science journals (*Nature*, *Science*, and *PNAS*)	65.1%	
Sociology journals (American Sociological Review and American Journal of Sociology)	2.5%	
Economics journals (American Economic Review and Quarterly Journal of Economics)	11.1%	
Psychology journals (Psychological Science and Journal of Personality and Social Psychology)	21.3%	
	N = 845	

[§]The vast majority of articles were penned by fewer than eight coauthors, and so all coauthors were invited to participate in our study. Collecting contact information for every coauthor on the rare paper penned by dozens of (and in one case, 204) coauthors proved intractable.

[¶]We included articles published over a shorter time period at *PNAS* than other outlets to avoid including dramatically more articles from *PNAS* than other journals, as *PNAS* publishes approximately the same number of articles in a week as *Nature* publishes in 6 mo.

Table 4. Means and SEs for scientific summary characteristics and correlations between summary characteristics

Variable	Mean	SD	LIWC positivity	Word count	Interesting	Usefulness	Reflects positively	Emotionality
Sharing likelihood	3.19	(1.88)						
LIWC positivity	0.02	(0.08)	1.00					
Word count	101	(53.3)	−0.20****	1.00				
Interesting	3.82	(1.85)	−0.04***	0.04****	1.00			
Usefulness	3.77	(1.79)	−0.04****	0.04****	0.68****	1.00		
Reflects positively	4.33	(1.19)	−0.03**	0.04****	0.46****	0.47****	1.00	
Emotionality	2.60	(1.61)	−0.02*	0.04****	0.60****	0.53****	0.37****	1.00
Comprehensibility	4.21	(1.75)	−0.05****	0.04****	0.55****	0.49****	0.34****	0.36****

*$P < 0.10$; **$P < 0.05$; ***$P < 0.01$; ****$P < 0.001$.

win a $50 Amazon gift card. The journals included in our sample were selected based on the following criteria: we first selected the three general science journals with the highest h5 indices on Google Scholar. Because these outlets published a limited number of social science articles, we added the two general psychology, sociology, and economics journals with the highest h5 indices on Google Scholar that publish research articles rather than review papers.

Eight hundred forty-five authors completed our survey (20.1% response rate; 20.7% for males and 18.6% for females). These authors described 474 unique scientific discoveries, and 231 unique discoveries were summarized by multiple coauthors. Table 3 provides descriptive statistics about the population of authors who participated.

Raters of Scientific Summaries. We recruited 7,664 participants to rate scientific summaries through Amazon's Mechanical Turk US worker pool and five large US universities' behavioral laboratories' online participant databases. In exchange for completing our short survey, participants were paid $0.50 on Amazon's Mechanical Turk (MTurk), $1.50 in one university participant pool, and entered in lotteries at other universities for Amazon gift cards such that their expected winnings were $0.50 (e.g., a 1% chance of winning a $50 gift card). At the outset of our survey, we included an attention check question ("what is 2+2?") following the best practices for online surveys outlined by Mason and Suri (38). Again following these best practices, we dropped all 186 participants who incorrectly answered this arithmetic question. This exclusion rule left us with 7,478 study participants. The average age of these raters was 30.7 (SD = 12.0); they were 49.4% male, 70.4% Caucasian, 13.2% Asian, 7.4% black, and 5.4% Hispanic. Half-a-percent had achieved less than a high school education, with 10.1% reporting their highest level of education was a high school diploma, 34.9% reporting some college, and the remainder reporting a college degree or higher. Five thousand, one hundred thirty-seven of these raters were recruited through MTurk, and 2,341 were recruited through US university behavioral laboratory subject pools. Note that these raters are not perfectly representative of those who attend to scientific research.

Procedures. ***Obtaining summaries of scientific discoveries.*** First, we gathered summaries of scientific papers from their authors using the survey method described above. These summaries served as our primary study stimuli. The first and primary question in the survey these authors completed was as follows:

> "**Research Summary**: We are interested in how people describe their research to others. In your own words, please provide a 3-5 sentence lay summary of your research paper entitled "[relevant paper title inserted here]". Keep in mind that your audience may not be scientists in your own area, or even scientists at all. So, try to describe your results in a way that a broad set of people could understand and find interesting."

After asking authors to provide a lay summary of their research, we asked them (*i*) how familiar they were with the paper in question (on a five-point scale from 1, "not at all familiar" to 5, "extremely familiar"), (*ii*) to tell us roughly what percentage of the total work that went into the paper they personally completed, and (*iii*) to provide us with some basic demographic information about themselves (primary research field, academic position, university name, sex, race, and birth year). Information about each scientist's discipline was also obtained by research assistants from scientists' departmental websites. Academics who indicated that they worked in the natural, physical sciences, and math (26.2% of our population), the life sciences (30.9% of our population), and the social sciences (31.2% of our population) were further classified into the following disciplinary subcategories based on their academic department affiliation: biochemistry, biology, chemistry, ecology, economics, genetics, mathematics, immunology, physics, psychology, and sociology, as well as other physical sciences, other life sciences, and other social sciences.

Obtaining ratings of scientific summaries. From a population of nonacademics, we next gathered ratings of the summaries of scientific discoveries we had collected. Raters who were recruited through MTurk and university subject pools completed a short survey entitled "Spreading the Word." They were told: "We are interested in the types of information that people share with others. Below is the summary of a recent scientific discovery published in a leading scientific journal. Please read the summary carefully:" Below these instructions, a randomly selected scientific summary from the set of 845 summaries obtained in our first survey of scientists was displayed. Participants were asked on a seven point scale: "How likely is it that you will share this scientific discovery with others?" (anchors: 1 = "very unlikely"; 7 = "very likely"; a variable we refer to as sharing likelihood). On the next page of the survey, raters were again provided with the same scientific summary and asked to rate it on a variety of different dimensions along seven-point scales. Specifically, they rated how comprehensible they found the summary (anchors: "not at all comprehensible"; "very comprehensible") (comprehensibility); how interesting they found the discovery (anchors: "not at all interesting"; "very interesting") (interesting); how useful they found the discovery (anchors: "not at all useful"; "very useful") (usefulness); how well it would reflect on them if they shared the discovery with others (e.g., would others think more or less of them?) (anchors: "It would reflect extremely negatively on me"; "It would reflect extremely positively on me") (reflects positively); and how much emotion it evoked (anchors: "very little emotion"; "a great deal of emotion") (emotionality). On the final page of the survey, we collected demographic information about raters (sex, age, race, and highest level of education achieved).

We obtained an average of 8.85 ratings per scientific summary (1st percentile = 3, 5th percentile = 5, 50th percentile = 9, 95th percentile = 14, 99th percentile = 16). Intrarater reliability was reasonable on all dimensions assessed. We ran one-way ANOVAs to compare ratings variation on each dimension assessed between scientific summaries with ratings variation within the same scientific summaries (39). Specifically, for sharing likelihood, the estimated reliability of the mean was 0.48, for comprehensibility it was 0.61, for interesting it was 0.59, for usefulness it was 0.55, for reflects positively it was 0.28, and for emotionality it was 0.43.

In addition to relying on human raters, we relied on automated sentiment analysis software to objectively quantify the positivity, emotionality, and frequency with which people were mentioned in each summary. Specifically, we relied on the widely used and well-established LIWC computer program (4, 40) to count (*i*) the total number of positive and negative words in each summary using a list of words classified as positive (e.g., love, nice, sweet) or negative (e.g., hurt, ugly, nasty) by human readers, as well as (*ii*) the total number of words in each summary referencing humans using a list of words classified as references to humans (e.g., adult, baby, boy) by human readers (41). This program also counted the total number of words (wordcount) in each scientific summary. Following Berger and Milkman (5), LIWC Positivity is calculated as the difference between the percentage of positive and negative words in an article, whereas LIWC Emotionality is calculated as the percentage of words that are either positive or negative. The frequency with which humans are mentioned is calculated as the percentage of words that contain a reference to a human. Table 4 provides means and SEs for, as well as correlations between, the primary summary characteristics analyzed.

Statistical Analyses. The primary outcome of interest is the rating of a scientific summary's likelihood of being shared with others. We evaluate what characteristics of a scientific summary's content, a summary's author, and a summary's rater predict the likelihood that the summary will be shared using ordinary least-squares (OLS) regressions.

We take two primary approaches to analyzing the data collected. First, we include one observation per rater, or 7,478 observations, and we predict a given rater's self-reported likelihood (1 = "very unlikely" to 7 = "very likely") of sharing a given summary while clustering SEs at the article level (producing 474 clusters). Second, we include one observation per scientific summary, or 845 observations, and we predict the average rating achieved by a given article with our regression. In these models, we use analytic weights to control for the fact that different numbers of raters contributed to the average rating of each summary. We report all of our primary results using both regression modeling approaches. In a subset of our regression models, our goal is to explore variation in reported sharing of the same scientific finding as a result of differences in the way different coauthors describe their finding. In these analyses, our OLS regressions include article fixed effects, or 473 fixed effects for the 474 unique articles summarized by scientists in our dataset.

Following standards in economics and psychology, we refer to P values from 0.10 to 0.05 as marginally significant and those <0.05 as significant throughout our statistical analyses. A type I error, or the incorrect rejection of a true null hypothesis, is of greater concern with marginally significant results.

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