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Research Report

Expressions of uncertainty in online science communication hinder information diffusion

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Abstract

Despite the importance of transparent communication of uncertainty surrounding scientific findings, there are concerns that communicating uncertainty might damage the public perception and dissemination of science. Yet, a lack of empirical research on the potential impact of uncertainty communication on the diffusion of scientific findings poses challenges in assessing such claims. We studied the effect of uncertainty in a field study and a controlled experiment. In Study 1, a natural language processing analysis of over 2 million social media (Twitter/X) messages about scientific findings revealed that more uncertain messages were shared less often. Study 2 replicated this pattern using an experimental design where participants were presented with large-language-model (LLM)-generated high- and low-uncertainty messages. These results underscore the role of uncertainty in the dissemination of scientific findings and inform the ongoing debates regarding the benefits and the risks of uncertainty in science communication.

Keywords: uncertainty, science communication, information diffusion, text analysis, social media

Significance Statement

Uncertainty is inherent in scientific research and scientists are strongly advised to transparently communicate uncertainty surrounding their research findings. We investigated whether incorporating uncertainty in the public communication of science can backfire by undermining its dissemination. We used natural language processing to measure uncertainty and large language models to experimentally manipulate uncertainty in social media posts about scientific findings. A field study of over 2 million social media posts about scientific findings and an experiment showed that more uncertain messages were shared less often. These results inform the ongoing debates regarding the benefits and the risks of uncertainty in science communication.

Introduction

Uncertainty is an integral part of scientific research. An open and transparent communication of uncertainty around scientific findings is a highly recommended research practice (1–4). Yet, science communicators (e.g. journalists) and scientists themselves are often reluctant to implement it (5–7). The widespread concern is that expressing uncertainty will undermine the public's trust in science and hinder the dissemination and implementation of scientific findings (7). While several studies examined the impact of communicating uncertainty on trust in science and yielded mixed results (8, 9), the question of whether uncertainty communication impacts the dissemination of scientific findings among the general public has not yet been considered by academic research. Addressing this question is important—after all, knowledge dissemination, i.e. transmitting the information to as large an audience as possible, is one of the primary goals of science communication.

A sizeable portion of the broader public now relies predominantly on social media platforms such as Twitter (currently known as X[a]) for information, including science news (10). As the impact of the news accessed via social media on individual decision-making, from voting to vaccination, can no longer be denied (11, 12), there is a growing need to understand how people share science news on social media. Herein, building on past research on the role of uncertainty and doubt in social behavior on digital platforms (13, 14) and the studies of uncertainty in science

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communication (9), we tested whether expressions of uncertainty in the public communication of scientific findings affect users' sharing behavior and, consequently, the findings' dissemination within online social networks. Specifically, we examined whether linguistic expressions of uncertainty in tweets sharing scientific findings predict retweet count and individuals' retweet intentions.

The present research has the following objectives. First, most studies on uncertainty communication in science explored the impact of uncertainty on the perception of research trustworthiness and science credibility (8, 9). We broaden this scope to encompass the potential influence of uncertainty on online sharing behavior (e.g. retweeting), shaping the science knowledge dissemination, also referred to as (information) diffusion. Second, prior studies examined the role of uncertainty in the perception of science in controlled laboratory or online experiments, using a limited number of stimuli tailored specifically for experimental purposes (8, 9). Here, we extend this research by taking a computational social science approach: we document the real-world consequences of uncertainty communication around scientific findings by examining the sharing behavior of millions of users of science news posted on Twitter (Study 1). We complement these large-scale field findings with experimental evidence by manipulating the level of uncertainty expression in social media posts in an online experiment and recording participants' intention to share these posts (Study 2).

Uncertainty in science communication and beyond

Uncertainty is inherent in every phase of the scientific process and consequently, all knowledge resulting from this process carries some degree of uncertainty. A transparent communication of uncertainty around scientific findings, such as acknowledging their boundary conditions and limitations of the methods used, has been promoted as one of the instruments to help science recover from the recent replication and credibility crisis (1, 2). Yet, humans do not like uncertainty. For example, according to the uncertainty intensification hypothesis (15), uncertainty amplifies the stress response to aversive stimuli (16) and increases the anxiety reaction to health risk estimates (17). Judgment and decision-making researchers suggest that people seem not to like uncertainty in experts either. For example, in the field of geopolitical forecasting and foreign policy, advisors are recommended to avoid explicit communication of uncertainty as numeric probabilities, even though this practice was shown to reduce predictive accuracy (18). Individuals tend perceive advisors who express uncertainty less favorably (19, 20). Uncertain advisors are often trusted to a lesser extent and perceived as less credible, as expressions of uncertainty are interpreted as signals of a perceived lack of competence and expertise (21).

It is therefore conceivable that expressions of uncertainty in science communication might undermine attributions of competence and the overall credibility of science. Several experiments showed that incorporating epistemic uncertainty (i.e. acknowledging the limitations and weaknesses behind the scientific methods) in the communication of scientific results might reduce trust in the source of the information as well as in the content itself (9). For example, learning that "there was some uncertainty around the (unemployment rate estimate), it could be somewhat higher or lower" decreased trust in this estimate (9). Yet, such detrimental effects were small and mostly limited to verbal (e.g. hedges, i.e. words such as appear, seem, likely, might or could) but not numerical (e.g. numerical ranges of estimates) expressions of uncertainty (8, 9, 22). Nevertheless, if uncertainty in science communication undermines the credibility of science as a whole, it will likely hinder the dissemination of scientific findings. Put differently: if the researchers themselves are not confident in what they found, why bother sharing their message with others?

Indeed, the inclusion of expressions conveying uncertainty has been associated with lower engagement with the message (i.e. sharing) in marketing and advertising. For example, including hedging expressions in corporate advertising and company communication was associated with lower user engagement, i.e. less content sharing online (23, 24). Also, online comments to New York Times articles featuring a higher prevalence of uncertain language were less likely to garner recommendations from readers (14). Taken together, this evidence suggests that uncertainty expressions in science communication would be associated with a lower level of dissemination.

Alternatively, there are also reasons to believe that expressions of uncertainty might foster, rather than undermine, dissemination. Models of social perception suggest that besides competence, attributions of morality (including trustworthiness and honesty) dominate social perception (25). While uncertainty might undermine the perception of competence, it might foster the perception of trustworthiness. There is evidence that people may perceive expressions of uncertainty as a signal of authenticity and trustworthiness. For example, consumers were shown to consider online restaurant reviews as more reliable when they were not overly positive and included some expressions of doubt (e.g. hedging) (13). Other studies showed that communicating uncertainty might have positive reputational benefits for authorities. For example, members of the US House of Representatives experienced higher public approval when incorporating expressions of uncertainty in their floor debates (26). Consequently, underscoring the uncertainty around their findings might benefit scientists and science communicators alike as well. Indeed, even though communicating uncertainty has been linked to a decreased perception of scientists' competence as experts in their field (27), it led to an increased perception of honesty and trustworthiness (27, 28). It is plausible that people are more inclined to share the information from the sources they consider trustworthy (29), resulting in a higher engagement with the scientific findings on social media in case they are communicated with a higher level of uncertainty.

At the same time, studies of users' content sharing behavior online have questioned the importance of message trustworthiness in determining sharing decisions (30). Specifically, misinformation researchers argue that there might be a disconnect between the information people trust and the information they share online. For example, in a series of experiments, headline veracity predicted perceptions of accuracy but was not related to sharing behavior (31). Finally, according to the studies on online language use, it is the linguistic features that render online posts most polarizing (e.g. moral–emotional words, negative valence words and verbal incivility) that emerge as the most influential predictors of information diffusion (32–38). Hence, it is conceivable that expressions of uncertainty will not matter for user sharing behavior of science news in social media networks. In summary, previous work provides equal support to three possibilities: incorporating uncertainty in the communication of scientific findings could (i) increase, (ii) undermine, or (iii) have no effect on its diffusion.

The present research

We test the implications of uncertainty communication in short social media posts about scientific findings on these findings' online dissemination. Study 1 applies a natural language processing (NLP) measurement approach (39) to quantify uncertainty in about 2 million of tweets presenting scientific findings and analyzes the sharing behavior of millions of users. Study 2 complements these field findings with an experiment where we manipulate the level of uncertainty expression in brief online messages and measure participants' intention to share them. The analysis plans of both studies were preregistered: https://osf.io/xwfah/?view_only=38756c5fbc9a4682bd2776170cc3f78e (Study 1) and https://aspredicted.org/76D_HKX (Study 2).

Study 1

In Study 1, we examined the effect of the level of uncertainty conveyed in messages about scientific findings on these findings' dissemination on social media, specifically, on Twitter. The same users could post multiple messages about scientific findings (indeed, in our study, about two thirds of the users provided more than one tweet), allowing us to disentangle the effects of user-level and tweet-level uncertainty. These effects are often referred to as between- (i.e. comparisons between users) and within- (i.e. comparisons between tweets of the same user) effects. Recent studies have highlighted the importance of distinguishing these two types of effects in multilevel data (40, 41). That is, if some users tend to post about science results with more uncertainty in general, this effect would be captured by the between-user parameter, whereas the within-user parameter can be interpreted as the effect of uncertainty in a specific message net of various user characteristics. Using a dataset of over 2 million tweets communicating research results we tested (i) whether tweets that express a higher degree of uncertainty are shared (retweeted) more or less often and (ii) whether users that tweet with a higher (vs. lower) degree of uncertainty, on average, receive more or fewer retweets. We used the Exploring Small, Confirming Big analytic strategy (42), wherein a limited portion of the data was utilized to formulate hypotheses and preregistration plans. Subsequently, these were tested in confirmatory analysis with the remaining out-of-sample data. Based on our literature review, we considered the possibilities of positive, negative, or no effect of uncertainty as equally plausible. Our examination of 10% of the data set apart for exploratory analyses provided some initial evidence for a negative effect of uncertainty on information diffusion.

Methods

Dataset

In January 2023, we downloaded 4,131,722 tweets posted between November 2017 and January 2023 using twitter API v.2 and the R package academictwitteR (43). This time frame was chosen as the twitter policy regarding the maximum number of characters in a tweet was kept constant during this time (before 2017 November, the number of allowed characters was 140, after 2017 November was280). We downloaded the tweets that contained at least one of the following research-related keywords or hashtags: "#studyresults", "#newpaper", "#newpaperalert", "study findings", "new paper", "research shows", "study results", "studies show", "study shows", "study suggests", "studies suggest", "research suggests", "research findings". Only original English-language tweets were downloaded (retweets and replies were not). Examples of tweets are shown in Table 1.

Table 1. Examples of tweets with high and low model-based uncertainty scores.

Tweet	Model-based uncertainty score
Studies have shown that cbd may help reduce chronic pain by affecting endocannabinoid receptor activity, reducing inflammation, and interacting with neurotransmitters. In addition, some research suggests that cbd may be effective for certain types of pain, including nerve pain.	5.42
There is increasing evidence linking climate change to the severe weather that gives rise to tornadoes. Further, emerging research suggests there may be a link between warming and large tornado outbreaks, particularly in the southeast in the winter.	5.36
Music therapy uses music to improve physical, emotional, and social well-being studies suggest it may help treat some mental health conditions, such as anxiety and depression. However, little research is available on music therapy and bipolar disorder.	5.33
A new study from Karnataka, India finds that 99.4% of the participants showed good immune response even 12 months after receiving the first booster dose of Covishield vaccine. The study proves that there is no need for second booster (fourth dose) of vaccine.	2.26
Evidence presented in court shows young people who have gender dysphoria need help and counseling. Research shows that there is no evidence that there is any psychological benefit from changing gender. This is a blow to the transgender extremists.	2.20
The study found that there was no major differences between the psychological adjustment of children in any of the groups of families, and scores were in the normal range for all.	2.34

Model-based uncertainty ranged from 1 = very uncertain to 7 = very certain ($M = 3.33$, $SD = 0.53$).

We cleaned the tweets in the following way: we removed URLs, user mentions, hashtags (including hashtag terms), punctuation, Unicode strings, "RT" at the beginning of tweets and trailing white spaces. We replaced "&" with "and", replaced new line characters with a space and turned all characters to lowercase. We removed tweets that were shorter than 5 words.

Out of 4,131,722 total tweets, 1,686,712 tweets contained texts that were posted at least twice (under different tweet IDs). Only unique tweets ($n = 2{,}441{,}158$) were retained for the analyses. We randomly selected 10% of the tweets for exploratory analyses and left the remaining 90% (holdout sample) for confirmatory analyses that were preregistered (multiple tweets from the same account could only be present in either the exploratory or the holdout sample, not both).

Measures

Our outcome variable is *information diffusion*, measured as the number of times a message was shared by other users (retweet count).

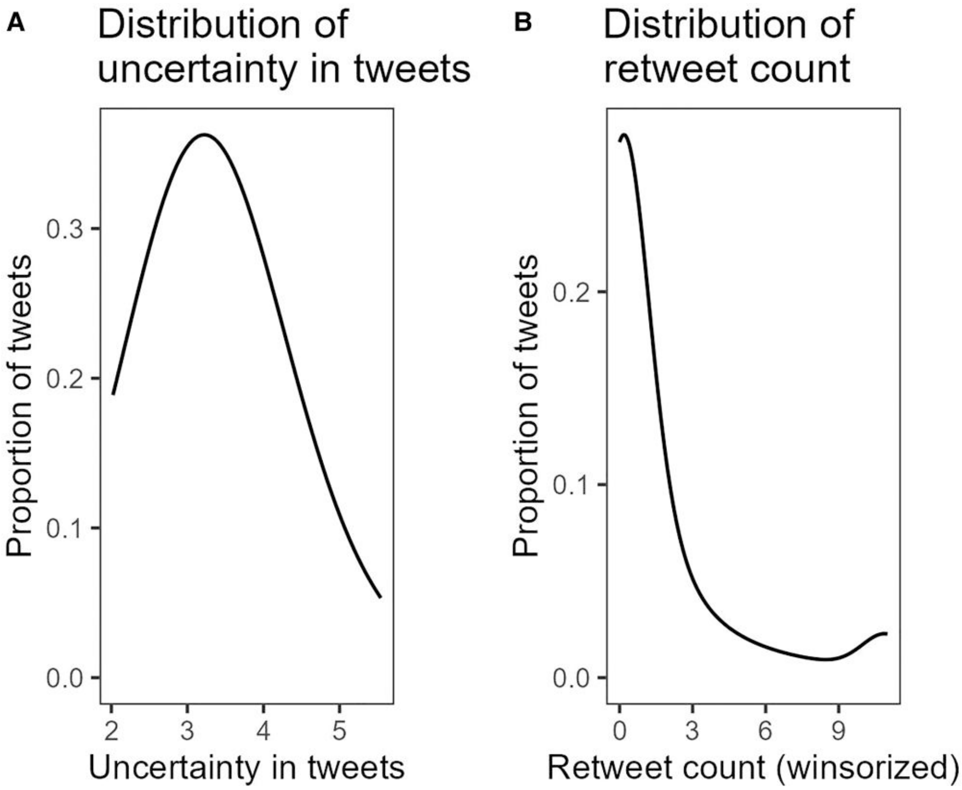

Fig. 1. Distribution of model-based uncertainty of tweets and retweet count. Holdout sample; Retweet count was winsorized for visualization (the top 5%) but was not transformed in the analyses; Uncertainty is shown as is (empirical range: 2.02 to 5.54).

Our main independent variable is the level of *uncertainty* expressed in tweets. To quantify expressions of uncertainty, we used a NLP model trained specifically to measure (un)certainty in the reports of scientific findings. The tool is based on the SciBERT language model and trained on a human-annotated (with respect to the level of certainty) corpus of scientific findings ($n \sim 2{,}200$) sampled from news and research abstracts (39). The model uses machine learning to predict the certainty score of an input text from its textual properties. We used the model that quantifies the sentence-level certainty, defined as "a unified perception of various information expressed in the given piece of text and [is] the primary judgment of certainty along a continuum from uncertain to certain" (39). For each text, the model provides a score between 1 (very uncertain) to 7 (very certain). We reverse-coded the score such that higher values indicate more uncertainty and refer to this measure as *model-based uncertainty*. The distribution of the model-based uncertainty is shown in Fig. 1. The model-based uncertainty score has a good construct validity as evidenced by a strong correlation with the uncertainty level provided by human annotators ($r = 0.63$ (39)).

Validation of the model-based uncertainty score

As the model was trained on scientific findings presented in news and scientific abstracts, we first tested whether the model can be used to assess uncertainty of scientific findings communicated on social media (specifically, Twitter). In contrast to news and scientific abstracts, Twitter imposes a character limit on posts and, as other online social media, Twitter posts are characterized by informal language and netspeak. We assessed the validity of the model-based uncertainty using two methods.

First, we assessed correlations with the percentages of tentative and certain words in a document (e.g. a tweet) computed by the Linguistic Inquiry and Word Count Software (LIWC, version 2015) (44). Following prior research, we averaged scores of tentativeness and (reverse-scored) certainty, resulting in a single indictor of LIWC-based uncertainty (13, 14). Using the exploratory data ($n = 232{,}770$), model-based uncertainty was positively associated with the LIWC-based measure of uncertainty at $r = 0.36$ ($P < 0.001$), see Supplementary Material for more details.

Second, we collected human ratings of the uncertainty of a subset of tweets to test if the model-based uncertainty score reflects the human perception of uncertainty well. We selected 100 tweets from the exploratory sample (50 tweets with the highest and 50 with the lowest certainty score[b]). We then recruited 252 participants from Prolific Academic and asked them to rate the tweets on uncertainty. Participants were either UK or US residents and had experience with Twitter (reported tweeting frequency of at least one to three times per week; we used Prolific prescreening service to preselect participants with Twitter experience). Twelve participants did not pass an attention check asking them to select a specific response instead of answering the question and were removed. To maximize inter-rater reliability, each participant rated 10 tweets and each tweet was rated by 25 participants (45). With respect to each tweet, participants indicated "how confident is this tweet" using a scale ranging from 1 = "very unconfident" to 7 = "very confident". We reverse-coded the responses such that higher values indicate more uncertainty. We computed the average uncertainty rating per tweet across the raters. Participants showed high agreement in uncertainty ratings (inter-rater reliability, two-way random model, average of multiple raters: 0.77). Importantly, model-based uncertainty was positively associated with participants' perception of tweet uncertainty, aggregated at each tweet (25 judgments per tweet): $r = 0.42$, $P < 0.001$, $n = 100$.

Tweet- and user-level uncertainty

Within-person uncertainty or tweet-level uncertainty was obtained by centering tweet uncertainty within twitter users (by subtracting user average uncertainty level). The tweet-level uncertainty effect reflects whether, for the same user, tweets with a higher uncertainty score yield less or more retweets than tweets with a lower uncertainty score. Between-person uncertainty or user-level uncertainty was obtained by averaging tweet-level uncertainty for each user. The user-level uncertainty effect reflects whether tweets written by users with a higher average uncertainty score yield less or more retweets on average than tweets written by users with a lower average uncertainty score (38, 46).

Control variables

Our analyses additionally included a number of control variables that were shown to predict retweet count in prior research (32). These controls included: word count (number of words in a tweet), number of longer (6 letters or more) words in a tweet, tweet publication year (2017 = 0, 2018 = 1 etc. until 2023), the number of followers of the twitter user (z-standardized). In addition, we controlled for several other linguistic characteristics associated with retweet count in prior studies: LIWC-measured negative emotions, LIWC-measured positive emotions and moral–emotional language. The latter was measured with the dictionary of moral–emotional words provided by Rathje et al. (34). Finally, as people could assign higher scientific value to the posts that sound analytically, we included LIWC-measured amount of analytical thinking (47).

Analytic strategy

Retweet count was highly skewed with most tweets receiving 0 retweets. The retweet count is an over dispersed count variable (i.e. a count variable with larger numbers of "0" responses). Thus, our primary analysis was a negative binomial regression model.

We estimated a series of multilevel negative binomial regressions with random intercept for tweet authors and a random slope of tweet-level uncertainty. We estimated two models: Model 1 included the effects of tweet-level and user-level uncertainty only. Model 2 added the control variables listed above. All control variables measured at the level of the tweet (except the publication year) were centered within users.

Following the preregistered analysis plan, we conducted several robustness checks: (i) we estimated Poisson regression models and (ii) we estimated linear multilevel model with log-transformed retweet counts as dependent variable (33).

Table 2. Means, standard deviations, and correlations among the language variables.

Variable	M	SD	1	2	3	4	5	6
1. Model-based uncertainty	3.33	0.53	—	—	—	—	—	—
2. Word count	25.53	11.09	0.24	—	—	—	—	—
			[0.24, 0.24]	—	—	—	—	—
3. Number of 6-letter+ words	28.07	11.87	−0.01	−0.14	—	—	—	—
			[−0.01, −0.01]	[−0.14, −0.14]	—	—	—	—
4. Analytic language	82.66	22.99	−0.10	−0.02	0.20	—	—	—
			[−0.10, −0.10]	[−0.02, −0.02]	[0.20, 0.21]	—	—	—
5. Positive emotion words	3.13	4.28	−0.04	−0.02	0.03	−0.09	—	—
			[−0.04, −0.04]	[−0.02, −0.02]	[0.02, 0.03]	[−0.09, −0.08]	—	—
6. Negative emotion words	2.00	3.56	0.05	−0.03	0.02	−0.04	−0.10	—
			[0.05, 0.05]	[−0.03, −0.03]	[0.01, 0.02]	[−0.04, −0.04]	[−0.10, −0.10]	—
7. Moral–emotional language	0.82	2.19	0.01	−0.03	−0.02	−0.05	0.24	0.28
			[0.01, 0.02]	[−0.03, −0.02]	[−0.02, −0.02]	[−0.05, −0.05]	[.24, 0.24]	[.28, 0.28]

$n = 2{,}162{,}661$; All coefficients are significant with $P < 0.001$; Tweet-level variables are untransformed (not user-centered like in the regression analyses); 95% CIs are in squared brackets.

Table 3. Negative binomial models, holdout sample.

	Model 1				Model 2			
Predictors	**IRR**	**CI**	**P**	**Effect size (% change)**	**IRR**	**CI**	**P**	**Effect size (% change)**
(Intercept)	1.21	1.15–1.26	**<0.001**	—	1.20	1.15–1.26	**<0.001**	—
Tweet-level uncertainty	0.95	0.94–0.96	**<0.001**	−2.0	0.90	0.89–0.91	**<0.001**	−3.9
User-level uncertainty	0.71	0.70–0.72	**<0.001**	−10.4	0.71	0.70–0.72	**<0.001**	−10.4
Word count	—	—	—	—	1.02	1.02–1.02	**<0.001**	12.1
Number of 6-letter+ words	—	—	—	—	1.001	1.00–1.00	**<0.001**	0.8
Publication year	—	—	—	—	1.01	1.01–1.02	**<0.001**	1.5
Follower count (z-standardized)	—	—	—	—	1.66	1.64–1.69	**<0.001**	66
Analytic language	—	—	—	—	1.0005	1.00–1.00	**<0.001**	0.7
Moral–emotional language	—	—	—	—	1.01	1.00–1.01	**<0.001**	1.6
Negative emotion words	—	—	—	—	1.001	1.00–1.00	**0.003**	0.3
Positive emotion words	—	—	—	—	0.99	0.99–0.99	**<0.001**	−3.0
No. of users			888,352				888,352	
No. of tweets			2,162,661				2,162,661	

IRR, Incidence Rate Ratio; All tweet-level variables were centered within users; Uncertainty range is 1–7 points; Word count indicates the number of words in a tweet; Number of 6-letter+ words indicates the number of words with 6 letters or more in a tweet; Analytic language is a summary score computed by LIWC that ranges from 1 to 100; Negative and positive emotion words indicate the percentage of negative and positive emotion words in a tweet; Moral–emotional language indicates the number of moral and emotional words in a tweet. Effect size indicates a predicted percentage change in retweet count associated with a 1 SD change in the predictor (e.g. a 1 SD increase in positive emotion words is associated with a 3% decrease in retweet count).

Results

Here we present the results of the analysis of the holdout sample. The results obtained in the exploratory sample are nearly identical and have been reported in the preregistration. Table 2 shows the correlations among the linguistic characteristics of the messages: uncertain tweets tended to be longer, contained less analytical language, fewer positive emotion words and more negative emotion words.

Table 3 shows the results of the negative binomial models predicting retweet count. Higher tweet- and user-level uncertainty was associated with lower retweet counts in both models, with and without the control variables. A 1-point higher (note that uncertainty's theoretical range is from 1 to 7 points) *user-level uncertainty* is associated with a 29% lower retweet count. As 1 SD of user-level uncertainty corresponds to 0.36 points, users whose tweets are on average 1 SD more uncertain tend to receive roughly 10% less retweets.

A 1-point increase in *tweet-level uncertainty* is associated with a 10% decrease in retweet count (Table 3, Model 2; 5% in Model 1). As 1 SD of tweet-level uncertainty corresponds to 0.39 points, for the same user, tweets with a 1 SD higher uncertainty score receive about 4% fewer retweets.

Among the control variables, follower count was correlated to more retweets; similarly, tweets containing more longer words, more analytical language, more moral–emotional language, more negative emotion words, less positive emotion words and tweets with a more recent publication date were predicted to receive more retweets (Table 3).

The alternative analyses employing a linear regression and Poisson model yielded comparable results leading to the same conclusions. These analyses are presented in the Supplementary Material.

To put the effect size of uncertainty in context, we compared it to the effects of the established predictors of retweet count in prior studies (32, 48). This comparison showed that, for the same user, tweets with a 1 SD higher moral–emotional language score or a 1 SD higher negative emotion language received about 1.6 and 0.3% more retweets, respectively (in comparison, a 1 SD lower uncertainty predicted 4% more retweets). Among nonlinguistic predictors, the follower count was the strongest predictor of retweets. Specifically, a 1 SD increase in follower count (i.e. 722,915 more followers) is associated with 66% more retweets. Hence, the effect of decreasing uncertainty by 1 SD on retweet count (~4%) is equivalent to the effect of having 42,717 extra followers (which is 34 times more followers than the median follower number: 1,246).

Study 2

While Study 1 demonstrated the role of uncertainty expressions for tweet dissemination in the field using over 2 million tweets presenting scientific findings, it could not ascertain any causal effect of uncertainty. Study 2 was designed to compensate for this shortcoming. In Study 2, we employed an experimental design where participants were randomly assigned to view either certain or uncertain social media messages presenting scientific findings. We then measured participants' intention to share these messages within their online networks.

Methods

Participants

We recruited 300 participants using Prolific. Seven failed an attention check item (the item presented a tweet "New research shows that people tend to stop buying IKEA furniture around age 34," followed by the question: "To monitor data quality, select 'Somewhat disagree' when responding to the following question") and were excluded, resulting in the final sample of 292 (144 males, $M_{age} = 38.55$, $SD_{age} = 12.38$).

For 9% of participants, the highest education degree achieved was high school, 38% had a Bachelor's degree, 23% had a Master's degree and 4% had a PhD. 16% work or used to work as a researcher at a university or another organization, another 15% worked in a field related to science, such as journalism, consulting, or education, and 68% had no connections with science or research. Most participants (48%) spent 30 min or less using Twitter daily, followed by 28% who spent between 30 min and 1 h and the remaining 24% of participants who spent 1 h or more. Informed consent was obtained from all participants.

Procedure and measures

From the dataset used in Study 1, we randomly selected 10 messages as stimuli. We created a high- and low-certainty version of each of these 10 messages by using the generative large language model ChatGPT that we requested to write a "certain" and an "uncertain" version of each message[c]. For example, for the original message "A recent study shows that the spore-forming probiotic GanedenBC30 may increase amino acid absorption from protein", the high-certainty version read "A recent study unequivocally demonstrates that the spore-forming probiotic GanedenBC30 significantly enhances amino acid absorption from protein", while the low certainty version read "A recent study suggests that the spore-forming probiotic GanedenBC30 might potentially enhance amino acid absorption from protein" (for all stimuli, see the Supplementary Material). We validated the obtained stimuli by scoring them on uncertainty using the same model-based uncertainty measurement approach as in Study 1 (39). As expected, high-certainty versions obtained markedly lower model-based uncertainty scores ($M = 3.32$, $SD = 0.30$) than low-certainty versions ($M = 5.19$, $SD = 0.26$) of each message, $t(9) = 15.91$, $P < 0.001$, $r = -0.96$, $d = 6.63$, 95% CI [4.30, 8.94].

The study used a mixed design where participants and messages were treated as random effects (49). Participants were randomly assigned to read either a low- or a high-certainty version of each message, i.e. each "source message" was only presented to the same participant once—either in the certain or uncertain version. Overall, each participant read five high-certainty and five low-certainty messages, and each message was rated by 30 participants.

Manipulation check

For each message, participants indicated how confident they found it, on a scale ranging from 1 = very unconfident to 7 = very confident.

Primary outcome measure

To measure *intention to share*, after each message, participants were asked whether they would consider sharing this story online (for example, through Facebook or Twitter). The response options ranged from 1 = "definitely not" to 7 = "definitely yes".

Secondary outcome measures

With respect to each message, we additionally measured participants' trust in the message ("How much do you trust the information in this tweet?"), their estimated utility ["How useful do you think the information in this tweet could be for your followers/

Table 4. Means, standard deviations, and correlations among participants' reactions to tweets, Study 2.

Variable	M	SD	1	2	3	4
1. Perceived uncertainty (manipulation check)	3.06	1.58	—	—	—	—
2. Trust	4.15	1.44	−0.58	—	—	—
			[−0.61, −0.56]	—	—	—
3. Intention to share	3.13	1.72	−0.38	0.56	—	—
			[−0.41, −0.35]	[0.54, 0.59]	—	—
4. Anticipated interest	3.61	1.82	−0.38	0.54	0.76	—
			[−0.41, −0.35]	[0.52, 0.57]	[0.75, 0.78]	—
5. Perceived utility	3.48	1.76	−0.38	0.58	0.78	0.87
			[−0.41, −0.34]	[0.56, 0.61]	[0.77, 0.79]	[0.86, 0.88]

$N = 2{,}920$; All coefficients are significant with $P < 0.001$; Perceived uncertainty (manipulation check) is recoded such that higher values indicate greater uncertainty.

friends (on social media)?"] and followers' interest in the information ["How interesting do you think the information in this tweet could be for your followers/friends (on social media)?"]. The responses to these items were given on a scale from 1 to 7, with higher values corresponding to higher trust, utility and anticipated interest.

Finally, participants responded to a number of socio-demographic variables: age, gender (1 = male, 2 = female, 3 = non-binary/third gender, 4 = prefer not to say), the highest degree completed (1 = some high school or less, 2 = high school diploma or GED, 3 = some college, but no degree, 4 = associates or technical degree, 5 = Bachelor's degree, 6 = graduate or professional degree [MA, MS, MBA etc.], 7 = PhD), political orientation (1 = extremely liberal, 10 = extremely conservative), Twitter use ("How much time do you on average spend using Twitter per day: 1 = 30 min or less, 2 = 30 min—1 h, 3 = 1—2 h, 4 = 2—3 h; 5 = 3 h or more) and connections to science ("How would you describe your connections with science/research? 1 = I work as a researcher at a university or another organization, 2 = I used to work as a researcher but do something else now, 3 = I work in a field related to science, such as journalism, consulting or education, 4 = I have no connections with science/research).

Results

First, we checked whether participants perceived low-certainty messages as less confident than high-certainty messages. A paired-sample t test showed that low-certainty messages ($M = 2.46$, $SD = 0.19$) were considered as expressing less confidence than high-certainty messages ($M = 3.65$, $SD = 0.39$), $t(9) = 9.57$, $P < 0.001$, $r = 0.90$, $d = 4.03$, 95% CI [2.44, 5.59]). Further, participants' ratings of message confidence were associated with model-based uncertainty scores, $r = -0.91$, $n = 20$, $P < 0.001$, providing further evidence for the construct validity of the uncertainty-scoring algorithm. For the correlations among all rating variables, see Table 4.

For hypotheses testing, we used multilevel regression models with participants' reactions to the tweets (e.g. intention to share) as dependent variable, and certainty condition (high vs. low) as independent variable. The model included random intercepts of participants and tweets. The results suggested that participants were less willing to share uncertain than certain messages ($d = 0.22$, $P < 0.001$), trusted uncertain messages less ($d = 0.39$, $P < 0.001$), anticipated them to be less useful ($d = 0.17$, $P < 0.001$) and less interesting to others ($d = 0.21$, $P < 0.001$). These results are shown in Fig. 2. Unstandardized regression coefficients and confidence intervals are presented in Table 5.

In a preregistered alternative model specification (see Supplementary Material), we used model-based uncertainty score (instead of condition) as independent variable. These alternative models further supported our conclusions: messages with a higher model-based uncertainty score were less likely to be shared, yielded less trust, anticipated utility, and interest from others.

For exploratory (not-preregistered) analyses, we estimated the same models (with the experimental condition as independent variable) with additionally controlling for participants' socio-demographic characteristics described in the methods and messages' linguistic features (the same as in Study 1): word count, count of longer (six letters+) words, use of analytic language, positive emotion words and negative emotion words (note that all messages had a score of 0 on moral–emotional language, eliminating it as a potential control variable). The results are shown in Table 5: if anything, adding these control variables rendered the effect of uncertainty stronger. Also, in contrast to Study 1, analytic language ($d = 0.27$, $P = 0.007$) and positive emotion words ($d = 0.49$, $P = 0.019$) were positively—not negatively as in Study 1—associated with the intention to share.

In the final set of exploratory analyses, inspired by the idea of a disconnect between trustworthiness judgment and sharing behavior (30), we examined whether trust in the message (vs. its anticipated utility and interestingness) predicted the intention to share the tweet. We regressed intention to share on trust, utility and interest, with participants and tweets modeled as random effects. All 3 variables were positively associated with the intention to share. Perceived utility of the information and the anticipated interest in the information from others were the strongest predictors (utility: $b = 0.30$, $P < 0.001$, $d = 0.58$; interest: $b = 0.33$, $P < 0.001$, $d = 0.67$, followed by trust in the information ($b = 0.19$, $P < 0.001$, $d = 0.47$). Trust indeed had the smallest effect on sharing, however, the differences between the coefficients of trust, interest and utility were not statistically significant ($P > 0.10$).

General discussion

Uncertainty is pervasive in scientific research and findings. Communicating uncertainty is a crucial step in addressing the credibility challenges faced by science (2) and allowing individuals and policy makers to make evidence-based decisions (4, 5, 50). Yet, scientists and science communicators alike seem hesitant in embracing uncertainty when they communicate research findings. For example, physicians only rarely discuss the uncertainty associated with the evidence supporting the medical decisions (51) and science journalists often prefer not to communicate uncertainty when reporting scientific findings to the public (6). Even in academic publications, linguistic expressions of uncertainty, such as hedging terms, have been reported to decrease in the last two decades (52), while the use of promotional terms (such as

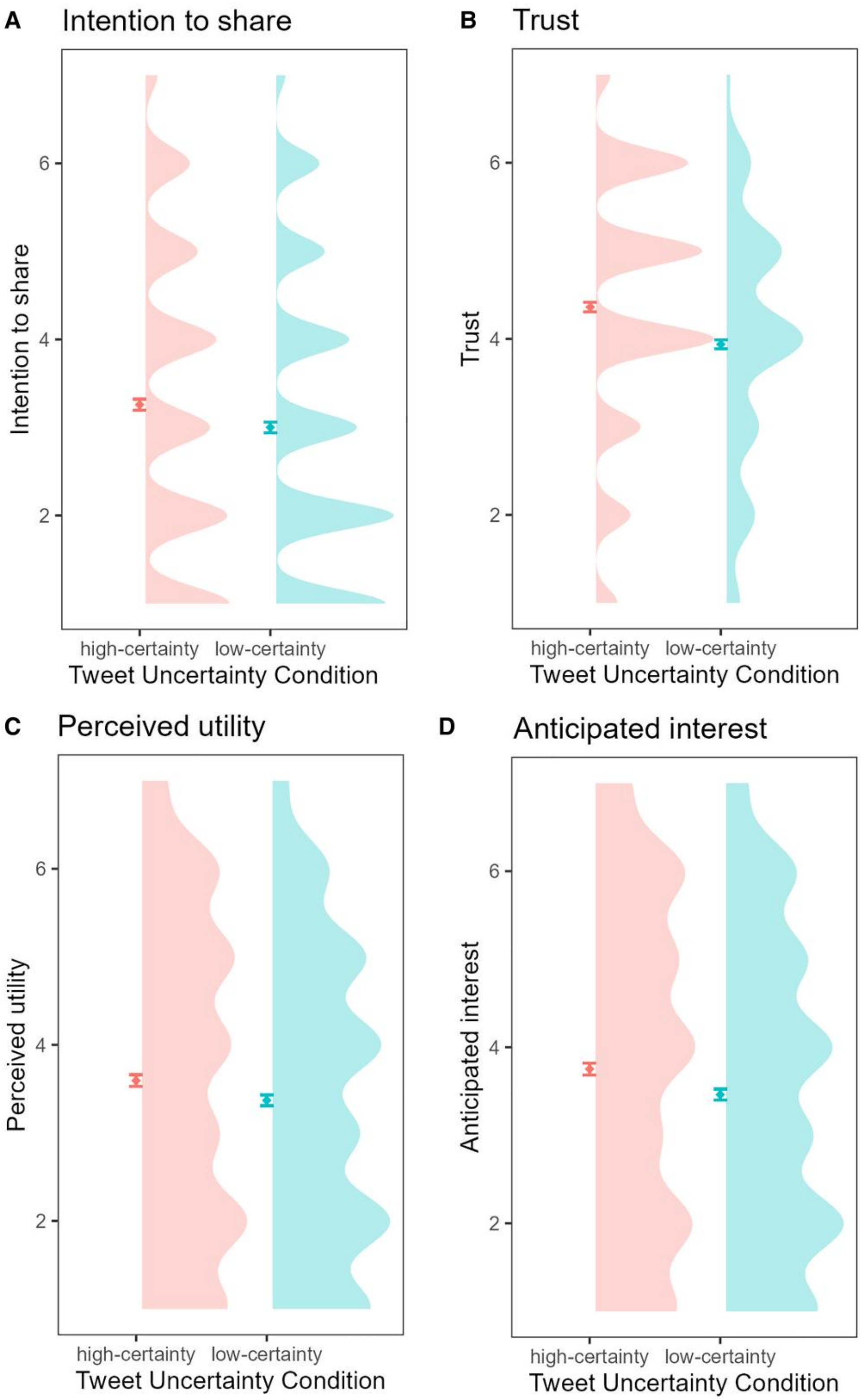

Fig. 2. Effect of the uncertainty condition on message perception and intention to share, Study 2. Big dots indicate average ratings per condition, error bars are 95% CIs.

"groundbreaking") has increased (53). Scientists might underestimate the public's ability to understand uncertainty (5) or believe that increasing transparency about uncertainty in the scientific processes will only "obscure the conclusions and seed unwarranted doubt in public perceptions" (7), ultimately hindering one of the primary objectives of science communication, namely knowledge dissemination.

Despite considerable research attention to the consequences of uncertainty for the perceived credibility of science (5, 8, 54), the possible implications of uncertainty for the dissemination of

Table 5. Effect of the uncertainty condition on message perception and sharing, Study 2.

Predictors	Intention to share			Trust			Perceived utility			Anticipated interest		
	Estimates	CI	P	Estimates	CI	P	Estimates	CI	P	Estimates	CI	P
(Intercept)	3.26	2.96–3.56	**<0.001**	4.38	4.24–4.52	**<0.001**	3.60	3.25–3.94	**<0.001**	3.75	3.40–4.11	**<0.001**
Uncertainty condition	−0.27	−0.36–−0.17	**<0.001**	−0.47	−0.55–−0.38	**<0.001**	−0.23	−0.33–−0.13	**<0.001**	−0.29	−0.40–−0.19	**<0.001**
(Intercept)	6.32	3.93–8.71	**<0.001**	6.27	4.38–8.15	**<0.001**	6.28	3.72–8.84	**<0.001**	5.45	2.83–8.06	**<0.001**
Uncertainty condition	−0.37	−0.60–−0.13	**0.002**	−0.49	−0.64–−0.34	**<0.001**	−0.31	−0.56–−0.05	**0.020**	−0.34	−0.61–−0.08	**0.010**
Participants' characteristics												
Age	0.00	−0.01–0.02	0.478	−0.01	−0.02–−0.00	**0.021**	0.00	−0.01–0.01	0.833	−0.00	−0.01–0.01	0.986
Gender	0.02	−0.28–0.31	0.917	0.02	−0.20–0.23	0.887	−0.13	−0.40–0.14	0.335	−0.16	−0.44–0.12	0.260
Political ideology	0.03	−0.04–0.11	0.384	−0.02	−0.07–0.04	0.571	0.02	−0.05–0.09	0.591	−0.00	−0.07–0.07	0.985
Education	0.03	−0.08–0.13	0.600	−0.00	−0.08–0.07	0.949	0.02	−0.08–0.12	0.718	0.02	−0.08–0.12	0.681
Twitter usage frequency	0.17	0.03–0.31	**0.019**	−0.03	−0.14–0.07	0.545	0.12	−0.02–0.25	0.088	0.12	−0.01–0.26	0.081
Connections to science: 2	0.15	−0.56–0.86	0.675	0.17	−0.34–0.69	0.508	0.09	−0.57–0.75	0.788	0.19	−0.49–0.87	0.590
Connections to science: 3	0.08	−0.54–0.71	0.797	0.27	−0.18–0.73	0.240	0.03	−0.55–0.62	0.907	0.23	−0.37–0.84	0.451
Connections to science: 4	−0.11	−0.68–0.47	0.719	0.25	−0.18–0.67	0.252	−0.15	−0.68–0.39	0.597	0.00	−0.55–0.56	0.990
Message characteristics												
Word count	−0.01	−0.02–0.01	0.499	0.00	−0.01–0.01	0.767	−0.01	−0.03–0.01	0.304	−0.01	−0.02–0.01	0.514
Six letter+ count	−0.00	−0.03–0.02	0.805	0.00	−0.01–0.02	0.629	−0.01	−0.04–0.02	0.494	−0.01	−0.04–0.02	0.671
Analytic language	−0.03	−0.06–−0.01	**0.007**	−0.02	−0.04–0.00	0.073	−0.02	−0.05–0.00	0.106	−0.02	−0.04–0.01	0.270
Positive emotion words	0.06	0.01–0.11	**0.019**	0.04	0.00–0.07	**0.037**	0.05	−0.00–0.11	0.066	0.07	0.01–0.13	**0.024**
Negative emotion words	−0.07	−0.18–0.04	0.227	−0.04	−0.10–0.02	0.231	0.01	−0.12–0.13	0.899	−0.00	−0.13–0.12	0.958

Estimates: unstandardized regression coefficients. Uncertainty condition: 1 = high uncertainty, 0 = high certainty. Connections to science: 2 = used to work as a researcher, 3 = work in a field related to science, such as journalism, consulting or education, 4 = no connections with science/research; 1 = currently work as a researcher at a university or another organization (reference category).

scientific findings remained unexplored so far. The present research sought to fill in this gap. In Study 1, using an NLP analysis of about 2 million tweets communicating scientific findings, we found that users, who routinely employ uncertain language in their tweets, are worse at information diffusion than those who refrain from using language reflecting uncertainty. The negative association between uncertainty and information diffusion also emerged at the level of tweets (i.e. within individuals): for a given user, tweets containing more uncertain language received fewer retweets, indicating a lesser extent of dissemination compared with tweets with more certain language. These effects held up when we controlled for other linguistic features shown to play an important role in information diffusion (here: moral and emotional words, negativity) (32, 48), as well as users' follower counts and tweet publication date.

In Study 2, we used an experimental design to establish the causal impact of uncertain language in sharing behavior. We used a large language model to generate a high- and a low- certainty version of each out of 10 preselected tweets. As a result, our stimuli conveyed the same science news story differing in the level of uncertainty. Consistent with Study 1, participants in Study 2 reported a lower intention to share messages with uncertain vs. certain language. Additionally, and replicating some of the prior findings (9), we documented lower trust, less perceived utility and diminished interest in uncertain (vs. certain) versions of the same message.

The present research has a number of strengths, including the use of computational text analysis. Additionally, it combines the ecological validity and the statistical power of an observational field study documenting the online behavior of millions of Twitter users (Study 1) with the precision and causal inferences afforded by a controlled experiment (Study 2). Furthermore, beyond testing the causal role of uncertainty on the intention to spread the message, Study 2 additionally explored the consequences of uncertainty for other dimensions of message perceptions (trust, utility, and interest) that could potentially explain the reluctant sharing behavior of uncertain messages.

Given the limitations of cross-sectional mediation analysis (55), we refrained from formally testing whether trust, utility, and interests mediated the effect of uncertainty on sharing decisions. However, the pattern of interrelations among these variables is consistent with the notion that users might view tweets containing uncertain scientific information as less valuable, less engaging and less credible, leading them to opt not to retweet such content. Other explanations of the links between uncertainty and sharing behavior are possible as well. For example, uncertainty around scientific findings might undermine perceived competence of the researchers (27), and diminish the public's willingness to engage with their findings. Also, even though lay people have a common shared understanding of everyday verbal expressions of uncertainty (56), there might be a mismatch between the level of uncertainty intended by the communicators and that perceived by the public. In a study of the perception of uncertainty in climate change reports, the public consistently misinterpreted the probabilistic statements in a regressive manner: people underestimated high probability and overestimated low probability (relative to the communicators' intentions) (57). These and other biases in how uncertainty is interpreted by the public (vs. intended by the communicator) might reduce the dissemination of scientific claims that contain language reflecting uncertainty.

Recent studies have shown that the effect of uncertainty on science credibility largely depends on the way uncertainty is expressed. The negative effect is primarily associated with "verbal uncertainty" (such as hedging), while numerical uncertainty (communicating ranges of estimates; also referred to as technical uncertainty) does not erode science credibility (8, 9). While the methods we used in the current paper did not distinguish between these two types of uncertainty, the way uncertainty was quantified here seems closest to verbal uncertainty, making our results consistent with this prior research. Another type of scientific uncertainty that has been associated with somewhat lower trust rates in prior studies is consensus uncertainty, which involves disagreement among scientists (8). Therefore, it would be valuable to investigate consensus uncertainty in the context of dissemination as well.

The present findings contribute to multiple streams of literature. First and foremost, we have shown that expressions of uncertainty might not only undermine the credibility of the message but also hinder its dissemination, thereby advancing the study of science communication. Second, we add to the literature on language predictors of information diffusion. Numerous studies have used various linguistic cues to predict the dissemination of information on social media, in the context of climate change (36), COVID-19 (58), health and medicine (59, 60) and even taxes (38). By revealing the role of uncertainty in retweeting behavior, our studies add uncertain language to the list of linguistic predictors of information diffusion. In addition, besides expressions of uncertainty, we uncovered further linguistic predictors of diffusion in the context of science communication: longer tweets and tweets with analytic language were more likely to be shared in Study 1 (however, note that this was no longer the case in Study 2, which is most probably due to the fact that Study 2 stimuli were specifically created to differ in uncertainty and not in other linguistic features). Importantly, in both studies, the uncertainty effect was robust against controlling for these linguistic cues. Finally, as generative AI such as large language models advances, there is a growing discourse on its applications in research (61, 62). In this study, we introduced an innovative approach by employing ChatGPT for the development of experimental stimuli. The effectiveness of this method was demonstrated through various validity analyses (human raters and a computational text-based measure of uncertainty).

We hope that the present findings will inspire further research in the field of science communication and the use of NLP to study online user behavior. For example, we showed that uncertainty in social media messages undermines their diffusion. This raises the question of whether any rapidly spreading online information, such as misinformation and fake news (63), likely contains more certain language. Misinformation prevention frameworks often build on the idea of fake news appealing to users' emotions (64) and indeed recent sentiment analysis of fake and real news showed fake news to use more emotional language (65). Future studies might explore whether high certainty expressions could be another linguistic footprint of fake news, explaining their propagation.

Another interesting avenue for future research is the question of the role of trust in online sharing behavior. It has been proposed that people's judgment of veracity of the information is irrelevant for their retweeting decisions (31). Yet, our data (Study 2) revealed that people intend to share findings they consider not only useful and interesting, but also trustworthy. At the same time, it is noteworthy that trust was not the most important predictor of sharing (if anything, it was the least important predictor), calling for more research into the role of trust and accuracy perceptions in online sharing decisions.

The results of the current paper suggest that including uncertainty qualifiers in science communication can undermine trust and online sharing behavior. Papers that receive more social media attention tend to have higher citation counts as well (66, 67). This observation raises the question of whether communicating uncertainty in academic publications might be "punished" in a similar manner, resulting in fewer citations and other indicators of attention from the academic community. It is important that future studies understand the boundaries of the uncertainty effect reported here.

Finally, do our results imply the scientists should shy away from expressing uncertainty around their findings? Certainly not. As some types of uncertainty expression (e.g. numerical or technical uncertainty) do not seem to bear the reputational costs of lower credibility (8), the question that we encourage scientists and science communicators to ask is not whether to report uncertainty or not but rather, how to do it. We hope that future studies will seek to further understand the intricacies of the different types and ways of expressing uncertainty in science communications, all while avoiding potential costs to research impact.

Notes

[a] We use the name Twitter here, as this was the platform's name at the time of data collection.

[b] We opted to this approach as a random selection of 100 out of over 230,000 tweets could lead to too many tweets from the lower end of the distribution (see Fig. 1) and would not include enough variance.

[c] We used the interface of ChatGPT 3.5 and the prompt: rewrite this text in a way that makes it sound more [less] certain.

Supplementary Material

Supplementary material is available at *PNAS Nexus* online.

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Author Contributions

O.S.: conceptualization, resources, data curation, formal analysis, investigation, methodology, writing-original draft, project administration. B.K.: conceptualization, methodology, writing-review and editing. A.E.: conceptualization, methodology, writing-review and editing. M.I.: data curation, writing-review and editing.

Data Availability

The analyses scripts, data and materials can be accessed at: https://osf.io/ye3b4/.

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