Research Article

Science Communication
1–25

DOI: 10.1177/1075547017731776
journals.sagepub.com/home/scx
SAGE

Using Expert Sources to Correct Health Misinformation in Social Media

Emily K. Vraga[1] and Leticia Bode[2]

Abstract

This study tests whether the number (1 vs. 2) and the source (another user vs. the Centers for Disease Control and Prevention [CDC]) of corrective responses affect successful reduction of misperceptions. Using an experimental design, our results suggest that while a single correction from another user did not reduce misperceptions, the CDC on its own could correct misinformation. Corrections were more effective among those higher in initial misperceptions. Notably, organizational credibility was not reduced when correcting misinformation, making this a low-cost behavior for public health organizations. We recommend that expert organizations like the CDC immediately and personally rebut misinformation about health issues on social media.

Keywords

misinformation, social media, health communication, credibility, CDC

Despite its ubiquity, social media is still a relatively new phenomenon, just over a decade old. It may not be surprising, then, that people, organizations, and institutions are still learning how to use it well. This is particularly true in the realm of science and health communication.

[1]George Mason University, Fairfax, VA, USA
[2]Georgetown University, Washington, DC, USA

Corresponding Author:
Emily K. Vraga, Department of Communication, George Mason University, 4400 University Drive, MS 3D6, Fairfax, VA 22030, USA.
Email: evraga@gmu.edu

Individuals are turning to online platforms to learn about science and health topics, with the Internet dominating as the primary source of information about science and technology news (National Science Board, 2016; see also Brossard, 2013; Pew Research Center, 2011). Moreover, such purposeful usage is only part of the picture; 37% of Facebook users regularly see news on Facebook about science and technology, and 46% see news about health and medicine (Pew Research Center, 2013).

At the same time, "online media offer scientists more opportunities to communicate directly with the general public rather than having to rely on journalists as mediators" (H. P. Peters, Dunwoody, Allgaier, Lo, & Brossard, 2014, p. 751). Scientists, health professionals, and organizations are sharing their research and engaging with the public about issues online (Brossard, 2013; Harris, Choucair, Maier, Jolani, & Bernhardt, 2014; National Science Board, 2016), and particularly on Twitter (Yeo, Cacciatore, Brossard, Scheufele, & Xenos, 2014). One report suggests that 47% of American Association for the Advancement of Science scientists use social media to discuss or follow science (Pew Research Center, 2015a), and when polled, a majority of U.S. scientists said they thought content in social networks could "strongly influence how the public thinks about science" (Allgaier, Dunwoody, Brossard, Lo, & Peters, 2013, p. 285).

However, the motivations underlying social media use differ for individuals versus organizations. Individuals primarily use social media for social purposes, but they often encounter news, politics, and health information while doing so (Bode, 2016; Diehl, Weeks, & gil de Zuniga, 2016; Pew Research Center, 2013; Vraga, Thorson, Kligler-Vilenchik, & Gee, 2015). Similarly, when the public engages with public health campaigns on social media, they often focus on social support, rather than treatment or prevention (Bravo & Hoffman-Goetz, 2016; Himelboim & Han, 2014; Neiger, Thackeray, Burton, Giraud-Carrier, & Fagen, 2013). In contrast, organizations—and particularly health organizations—use social media to push content to online audiences, which can limit participation among or interaction with members of the general public (Chung, 2016; Duke, Hansen, Kim, Curry, & Allen, 2014; Park, Rodgers, & Stemmle, 2013).

Both types of users—individuals and organizations—confront a particular challenge when faced with the prevalence of bad information on social media. Many have criticized social media for creating spaces in which misinformation is easily spread but difficult to refute (Bessi et al., 2015; Lewandowsky, Ecker, Seifert, Schwarz, & Cook, 2012; Sharma, Yadav, Yadav, & Ferdinand, 2017). This concern with misinformation has spiked in the wake of 2016 U.S. presidential election, when "fake news" entered the public lexicon. Nearly one third of American adults say they often see political news online that is completely made up, and a quarter say they have inadvertently or intentionally shared made-up news online (Pew Research Center, 2016). This raises several questions: When individuals sees falsehoods touted as truth on social media, what should they do? If they correct them, will it matter? Or are organizations better suited to playing a corrective role in this space? And how is the credibility of either of these actors affected by the choice to intervene?

This project seeks to answer these questions, offering practical insights for individuals and organizations about how to respond to bad information on social media. While existing research has begun to look at these questions (Bode & Vraga, 2015; Fung et al., 2016; Jong & Dückers, 2016; Vraga & Bode, 2017), we expand on it in two major ways. First, we consider the impact of the *number* of corrections offered to a post including misinformation to determine at what point it no longer helps to offer additional correction. Second, we consider the *source* of corrections to provide tailored recommendations for different types of social media users.

We test these questions using the Zika pandemic as a case study. By fall of 2016, although scientists had broadly reached consensus about the causes of Zika and its effects, misinformation about its origins and its effects had spread and gained popularity online (Al-Qahtani, Nazir, Al-Anazi, Rubino, & Al-Ahdal, 2016; Dredze, Broniatowski, & Hilyard, 2016; Sharma et al., 2017; World Health Organization [WHO], 2016). Misinformation about the virus was particularly prolific on social media. One study found that pseudoscientific claims about the causes of Zika on Twitter tended to coincide with media attention and interest (Dredze et al., 2016), while another found that even though misinformation about Zika occurred in a minority of posts on Facebook, those incorrect posts tended to receive the most public engagement (Sharma et al., 2017). Therefore, misinformation surrounding Zika was clearly an issue on social media.

To determine who can best correct misinformation, how to do so, and at what cost, we employ an experimental design in which respondents are exposed to a simulated Twitter feed that includes false information about the origins of the Zika virus. They are then confronted with a refutation of that misinformation. We systematically manipulate whether that correction comes from the Centers for Disease Control and Prevention (CDC; 2016), from another unknown Twitter user, or from both. The CDC is particularly important to study, as it was the most positively viewed governmental agency in the United States as of 2015, with 70% rating it favorably (Pew Research Center, 2015b) and had a history of sharing information about outbreaks on Twitter (Dalrymple, Young, & Tully, 2016). Moreover, the CDC was one of the top two organizations disseminating health information on Twitter during the beginning of the Zika outbreak in early 2016 (Stefanidis et al., 2017), positioning it to potentially correct misinformation as it emerged on the issue.

Literature Review

Although definitions of misinformation abound (see Giglietto, Iannelli, Rossi, & Valeriani, 2016, for an overview), we use a commonly cited definition originated by Nyhan and Reifler (2010): "Cases in which people's beliefs about factual matters are not supported by clear evidence and expert opinion" (p. 305). This definition is particularly appropriate for studying scientific issues, where consensus among the scientific community offers relatively clear boundaries between correct and incorrect information. Note, too, the difference between misinformation—incorrect information—and misperceptions—the belief in misinformation. Both misinformation and misperceptions are rampant in the American media environment (Jerit & Barabas, 2012; Leiserowitz, Maibach, Roser-Renouf, & Hmielowski, 2012), and particularly online (Kata, 2010), making this topic one of great importance to study.

Although some research emphasizes the difficulty of altering misperceptions (Nyhan & Reifler, 2010; Thorson, 2016), recent work has begun to document methods to successfully correct misinformation. Studies have suggested that corrective advertisements can reduce misperceptions that arise from incorrect claims in drug advertisements, even months after the original exposure (Aikin et al., 2015; Aikin et al., 2017). Likewise, corrective information from fact-checking organizations can reduce beliefs in incorrect information (Amazeen, Thorson, Muddiman, & Graves, 2016; Garrett, Nisbet, & Lynch, 2013), although such debunked misinformation may still negatively affect perceptions of their target (Thorson, 2016).

We argue that social media may be an especially rich place for correction to occur. Southwell and Thorson (2015) suggest misinformation is particularly problematic as it can be expensive and difficult to ensure corrections reach the populations who saw the misinformation. Social media may offer a space for correction to occur immediately, mitigating this concern. Additionally, the emphasis on social interactions online may reduce barriers to correction that are likely to occur in more overtly politicized spaces (Ellison, Steinfield, & Lampe, 2007; Messing & Westwood, 2014), creating a space where observational correction—when an individual updates their own attitudes after seeing *another* person corrected—is more feasible. Previous work has found that observational correction can take place via mechanisms built into social media platforms, like the related stories algorithm on Facebook, which promotes stories similar to the original shared link (Bode & Vraga, 2015). Social corrections—from other social media users—are also effective for reducing misinformation, at least (1) when there are multiple corrections and (2) when users cite a source for their corrective information; these results hold across both Facebook and Twitter (Vraga & Bode, 2017).

However, existing research on social media has only considered multiple instances—that is, two separate sources—of correction. It remains to be seen how many corrections it takes for misperceptions to be reduced online. We expect this process of whether a single correction is effective in reducing misperceptions will depend on the *source* of the correction.

For other Twitter users, it is unclear whether a single corrective response to misinformation will be sufficient to mitigate misperceptions. On the one hand, previous research suggests that two unknown users can successfully correct misperceptions when they provide a source to correct incorrect statements (Vraga & Bode, 2017). This may result from the power of social cues; previous research suggests social cues that accompany news stories, such as endorsements or comments, can influence which stories are selected (Messing & Westwood, 2014), perceptions of its credibility (Metzger, Flanagin, & Medders, 2010), or the persuasive impact of the story (Winter, Bruckner, & Kramer, 2015). Given that social motivations—such as the desire to develop and maintain online relationships—underscore sharing and consuming news via social media (Choi, 2016; Hermida, Fletcher, Korell, & Logan, 2012; C. S. Lee & Ma, 2012), other users may be especially trusted as a source of corrective information. Conversely, these same social motivations may discourage people from posting corrective information to avoid potential conflict with friends and family online, especially for contentious social issues (Vraga et al., 2015).

On the other hand, the strength of the correction is lessened for a single user correction, given that it is not repeated (Lewandowsky et al., 2012). Indeed, when a correction is paired with a statement that repeats misinformation, the correction is not particularly effective (Bode & Vraga, 2015). Moreover, the misinformation itself is being spread by another social connection, which may make it difficult to discern *which* user should be trusted when the users are at odds over the correct information, given that both provide a link to a seemingly-credible source. The social motivations to create conversation or share interesting information are also linked to sharing misinformation on social media (Chen, Sin, Theng, & Lee, 2015) may undermine these social cues. Given these competing expectations, we offer our first research question:

> **Research Question 1:** Will a single correction from another user be effective in reducing misperceptions regarding the causes of the Zika virus compared to a control condition?

For a reputable organization like the CDC, a single correction of misinformation may be sufficient to negate its effects on misperceptions.

Research that looks at correction of misperceptions more broadly, rather than specifically in the social media context, often relies on expert correction (e.g., Garrett et al., 2013; Lewandowsky et al., 2012; Nyhan & Reifler, 2010). Such an approach has its roots in credibility research, which suggests that expertise is an important component of credibility—and that such credibility tends to heighten the persuasive impact of the communication (Austin & Dong, 1994; Chaiken & Maheswaran, 1994; Eastin, 2001; Hovland & Weiss, 1951). Moreover, credibility cues are particularly relevant when people are not motivated to process information, and this heuristic route tends to dominate online (Chaiken, 1980; Chaiken & Maheswaran, 1994; Metzger, 2007; Metzger et al., 2010). Because government institutions like the CDC are generally well-respected and deemed to be credible information sources (Pew Research Center, 2015b), we anticipate the following:

Hypothesis 1a: A single correction by the CDC will be effective in reducing misperceptions regarding the causes of the Zika virus compared to the control condition.

Hypothesis 1b: A single correction by the CDC will be more effective in reducing misperceptions regarding the causes of the Zika virus compared to a single correction by another social media user.

Previous research supports that two corrections on social media—whether from a Facebook algorithm or from another user providing a link to an external source—can be successful in mitigating misperceptions for emerging issues (Bode & Vraga, 2015; Vraga & Bode, 2017). However, in these studies, the sources of both corrections were held constant. Here, we consider whether the order of the source of correction matters. In other words, should a social media user also correct misinformation if the CDC has already done so? Should the CDC reinforce a correction offered by another user?

Hypothesis 2: Two statements of correction will result in decreased misperceptions compared to a control condition regarding the causes of the Zika virus, no matter their order.

Research Question 2a: Does a correction by the CDC following a correction by another user result in decreased misperceptions as compared to correction by another user alone?

Research Question 2b: Does a correction by another user following a correction by the CDC result in decreased misperceptions as compared to correction by the CDC alone?

Credibility

We also consider the effect of corrective intervention on social media on the evaluations of the corrector. That is, we might expect that people's opinions of the person or institution doing the correction would be affected by the act of correcting. This might go in either direction—either one's evaluations are enhanced because one is acting as an expert arbitrator or one's evaluations might be negatively affected for butting into a conversation uninvited.

The possibility of negative effects may be part of what prevents institutions and organizations from stepping in on social media more often than they currently do, making this an important component to study. Many scientists shy away from engaging in behaviors that may be classified as "advocacy," particularly when the issue is political (Fischhoff, 2007; Kotcher, Myers, Vraga, Stenhouse, & Maibach, 2017; Nelson & Vucetich, 2009), even as the public and scientists often agree that scientists should be engaged in public discussions about policy (Pew Research Center, 2015c). Even if we show that correction by such institutions is effective, these organizations may still be unwilling to engage in corrective action if they are likely to pay a price in terms of their credibility with the public. For this reason, we test the credibility evaluations of the CDC. We again pose a research question, as we can imagine two competing effects. If the public perceives such corrections as inappropriate, they may see the organization as less credible as a result. Alternatively, they may reward an organization for performing a public service to correct misperceptions as they arise online. Therefore, we ask,

> **Research Question 3:** Will correcting misinformation influence perceptions of the credibility of the CDC?

Similarly, individuals may be hesitant to correct others' misinformation in a social setting like Twitter, concerned they might be evaluated negatively by their peers. Alternatively, they might be evaluated more positively for stepping in and offering expertise in their correction.

> **Research Question 4:** Will correcting misinformation influence perceptions of trustworthiness of other users who comment on news stories on Twitter?

The Moderating Role of Initial Misperceptions

Finally, we investigate the role of previously held beliefs in affecting correction. In general, misperceptions become harder to correct as they become more deeply engrained in an individual's identity, leading people to engage in more motivated reasoning that serves to protect current beliefs, even against corrective information (Lewandowsky et al., 2012; Nisbet, Cooper, & Garrett, 2015; Nyhan & Reifler, 2010). For this reason, previous research has suggested that corrections on social media may be effective for relatively new or novel issues such as the relationships between GMO (genetically modified organism) foods and illness but are unable to overcome deeply established beliefs on controversial issues like the relationship between vaccinations and autism (Bode & Vraga, 2015). However, it is unclear whether misinformation about the causes of Zika has risen to this level of belief that will engender strong barriers against correction. Therefore, those highest in initial misperceptions might be most difficult to persuade, but they also have the farthest to go in terms of movement on the issue—those who already hold correct perceptions should exhibit a ceiling effect. Our final question therefore asks how initial misperceptions affect the extent to which misperceptions are reduced. If correction happens only at low levels of initial misperceptions, it would still be a positive finding, but it might suggest that correction is not reaching those who need it most.

> **Research Question 5:** Does the level of initial misperceptions influence the effectiveness of corrective information depending on its source, order, and number?

Method

To test our expectations, we recruited participants from required introductory courses of a large mid-Atlantic university in the fall of 2016. Students were offered extra credit for taking an experiment embedded in an online survey. The total sample included 1,384 valid responses.[1] Participants were an average of 19 years old (M = 19.40, SD = 2.97), underclassmen (82.4%), roughly divided by gender (52.9% female), and relatively diverse (51% White, 15% Black, 21% Asian, 12% Latino).

After answering a short pretest survey, all participants viewed a simulated Twitter news feed made up of four tweets (see the appendix). Twitter was chosen because it is commonly cited as a major source of misinformation in the social media world (Castillo, Mendoza, & Polete, 2011; Oyeyemi, Gabarron, & Wynn, 2014; Starbird, Maddock, Orand, Achterman, & Mason, 2014) and the most commonly used social media platform by science researchers (Yeo et al., 2014). Participants were asked to take their time reading through the feed as they would be asked questions about their experience and were required to spend 10 seconds on the page before they could continue.

Within the Twitter feed, participants were randomly assigned to one of nine experimental conditions that manipulated the second post of the feed.[2] We focus on five those conditions for this study. In the *control* condition, the second post is a link to a news story about housing prices in the local area. For the other four conditions, the second post is a link to a false news story about the Zika outbreak in the United States, with the story and the original poster claiming that the outbreak was caused by the release of GMO mosquitoes.[3] Participants in those conditions were exposed to a response that corrected the misinformation, and we manipulated the source and number of replies: from a *single user*, from *the CDC*, from *a user followed by the CDC*, and from *the CDC followed by a user*. For the misinformation tweet and the corrective response, we selected gender neutral names to avoid a potential gender bias in credibility.[4] In all cases, the response included a link to the CDC website containing Zika information and the hashtag #zika. Given research that shows that people pay attention to and rely on comments when evaluating news, we are confident that participants will process the content from the corrective replies (Winter & Kramer, 2016). After viewing the simulated feed, participants answered a posttest survey before being thanked for their participation and debriefed that the Twitter feed was created by researchers and that the scientific consensus is that GMO mosquitos are not to blame for the Zika outbreak (CDC, 2016; WHO, 2016).

Measures

Misperceptions About Zika

In the pretest, participants rated their level of agreement on a 7-point scale with three statements designed to tap into their knowledge about the cause of the Zika outbreak: "The release of GMO mosquitos caused the Zika outbreak," "GMO mosquitos are to blame for the spread of the Zika virus," and "The Zika outbreak was caused by natural factors" (reversed). These items were obscured among attitudes about other issues, such as climate change or home prices. These three items were combined into an index, with a higher score indicating greater misperceptions about the cause of the Zika virus ($\alpha = .68$; $M = 3.69$, $SD = 0.91$). In this sample, 20.1% of participants initially held misperceptions about the causes of the Zika virus, 39.1% were neutral on the causes, and 40.8% held correct attitudes.[5] These same items were repeated in the posttest ($\alpha = .76$, $M = 3.55$, $SD = 0.96$), where 15.3% held misperceptions, 40.5% were neutral, and 44.2% held correct attitudes. A subtractive score calculated change in Zika misperceptions, with a lower score indicating reduced misperceptions ($M = -0.14$, $SD = 0.75$).

CDC Credibility

We used a single item indicator in the posttest that asked participants to report how credible they found the CDC as a source of information on a 7-point scale from *not credible at all* to *extremely credible* ($M = 5.98$, $SD = 1.30$). Participants who selected an eighth response option with an eighth response option of “not familiar with” the CDC ($n = 92$) were excluded from this measure.

User Trustworthiness

For other users, we test trustworthiness instead of credibility. Previous research shows the trust and credibility are linked, tapping into roughly the same construct (Kim, 1967; R. G. Peters, Covello, & McCallum, 1997). Thus, we translate the idea of credibility to trustworthiness for these users. Participants reported how much they trusted people who comment on news stories on Twitter on a 5-point scale, from *not at all* to *completely* ($M = 1.90$, $SD = 0.78$).

Results

To test our first set of expectations about the effectiveness of a single correction in reducing misperceptions, we use a one-way analysis of covariance (ANCOVA), controlling for existing misperceptions on the Zika issue and for the message wording factor. The omnibus ANCOVA test suggested that the effect of correction type is significant in predicting change in Zika misperceptions, $F(4, 1379) = 3.03$, $p = .02$, partial $\eta^2 = .009$ (Figure 1). To answer our specific research questions and hypotheses, we examined the pairwise comparisons using a least significant difference adjustment, applying a one-tailed test for all hypotheses and a two-tailed test for all research questions. In response to Research Question 1, we found no significant decrease in Zika misperceptions in the *user-only* correction compared to the control condition ($p = .79$). However, the *CDC-only* correction significantly reduced misperceptions, compared both to the control ($p = .05$ as one-tailed test; supporting Hypothesis 1a) and to the user-only correction ($p = .01$; supporting Hypothesis 1b).

Our second hypothesis suggested that providing two corrections of misinformation will reduce misperceptions compared to the control, no matter their order. We found mixed support for this hypothesis. Specifically, the *social plus CDC* correction led to a significant decline in misperceptions as compared to the control ($p = .02$), but there was only a marginally significant difference between the control and the *CDC plus social* correction ($p = .08$).

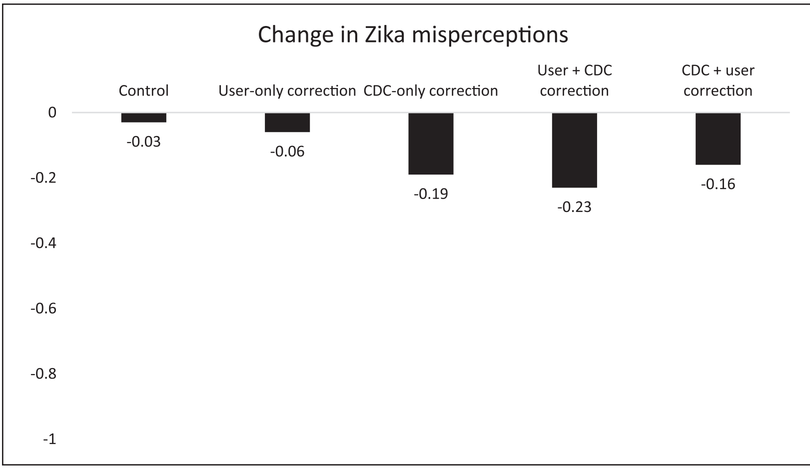

Figure 1. Main effect of correction type on change in Zika misperceptions.
Note. CDC = Centers for Disease Control and Prevention.

Our second set of research questions compared the addition of a second correction after another user or organization has corrected the information. For Research Question 2a, we found that adding a second correction from the CDC after a user has corrected the misinformation further reduces Zika misperceptions compared to the *user-only* condition ($p < .01$), whereas adding a second user correction after the CDC has corrected the misinformation did not decrease misperceptions compared to the *CDC-only* condition ($p = .66$).

Credibility and Trustworthiness

Next, we explored whether the act of correcting misinformation on social media influenced perceptions of the credibility of the source of the correction—either other users on Twitter or the CDC. Our results present a consistent picture. A one-way ANCOVA controlling for existing misperceptions and for the second experimental manipulation of message type found no effect of correction type on perceptions of other users' trustworthiness, $F(4, 1380) = .26$, $p = .90$, partial $\eta^2 = .001$, or on perceptions of the CDC's credibility as a source of information, $F(4, 1882) = 1.28$, $p = .28$, partial $\eta^2 = .004$. Therefore, correcting misinformation as it arises on social media does not appear to harm or improve either the credibility of the CDC as an informational source or the trustworthiness of another user.

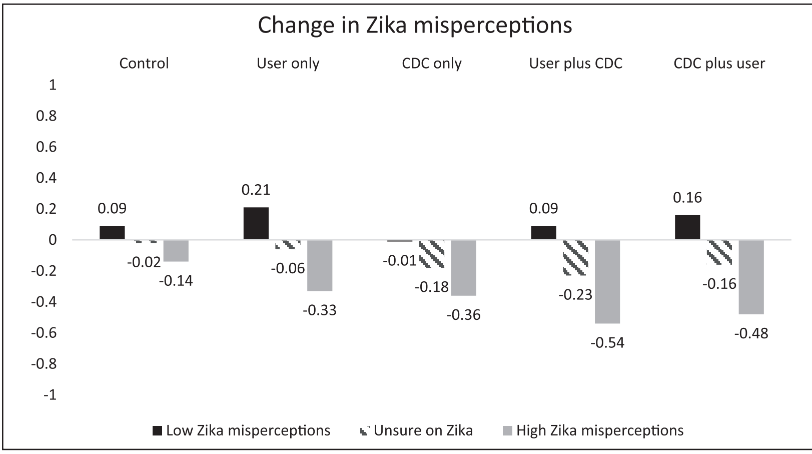

Figure 2. Conditional effects of correction type on Zika misperceptions depending on initial Zika beliefs.
Note. CDC = Centers for Disease Control and Prevention. Categories of initial misperceptions defined as follows: 1 *SD* below mean as low initial Zika misperceptions (*M* = 2.79), the mean is unsure (*M* = 3.69), and 1 *SD* above the mean as high Zika misperceptions (*M* = 4.60), as measured on a 7-point scale. Values in the figure indicate the estimated marginal means for each group in each experimental condition.

Moderating Role of Preexisting Attitudes

Our final set of research questions tested whether preexisting misperceptions toward Zika moderated the relationship between type of correction, change in misperceptions, and evaluations of the source of the correction. To do so, we used the PROCESS macro (Model 1) to test whether the comparison between each correction condition and the control condition depends on initial misperceptions (Hayes, 2013), controlling for message type. The PROCESS model suggested this is the case (Figure 2; Table 1). Specifically, there was a significant interaction between correction type and initial Zika misperceptions in three of the four conditions: the *user-only* ($b = -.17$, $SE = .08$, $p = .03$), the *CDC plus user* correction ($b = -.22$, $SE = .08$, $p < .01$), and the *user plus CDC* correction ($b = -.23$, $SE = .08$, $p < .01$); this interaction was only nonsignificant for the *CDC-only* correction ($b = -.07$, $SE = .08$, $p = .41$). Moreover, the pattern of effects was consistent across comparisons: Each type of correction was more effective in reducing misperceptions among those higher in initial Zika misperceptions.

Next, we change the reference group to compare how the *social-only* and *CDC-only* conditions compared to the conditions where a second corrective

Table 1. Conditional Effect on Reduction in Misperceptions of Correction Type (Compared to Control) and Initial Levels of Zika Misperceptions.

Initial Zika attitudes	User, *b* (*SE*)	CDC, *b* (*SE*)	User plus CDC correction, *b* (*SE*)	CDC plus user correction, *b* (*SE*)
Low Zika misperceptions[a]	.12 (.12)	−.10 (.12)	−.01 (.12)	.07 (.12)
Relatively unsure	−.04 (.09)	−.16† (.09)	−.21* (.09)	−.14 (.09)
High Zika misperceptions	−.19† (.12)	−.22† (.12)	−.41*** (.12)	−.35*** (.12)

Note. CDC = Centers for Disease Control and Prevention. Table provides unstandardized beta coefficients comparing each experimental treatment group with the control condition, with standard errors in parentheses.

[a]Categories of initial misperceptions defined as: 1 *SD* below mean as low initial Zika misperceptions (M = 2.79), the mean is relatively unsure (M = 3.69), and 1 *SD* above the mean as high Zika misperceptions (M = 4.60), as measured on a 7-point scale.

†$p \le .10$. *$p \le .05$. **$p \le .01$. ***$p \le .001$.

response is added. When we contrasted the *social-only* and *social-plus CDC* conditions, we did not find that initial Zika misperceptions moderate this relationship ($b = −.05$, $SE = .06$, $p = .38$). However, comparing the *CDC-only* to the *CDC plus social* response, we found a significant interaction with initial Zika misperceptions ($b = −.16$, $SE = .07$, $p = .01$), and in this case adding a second user response to the CDC response actually *increases* misperceptions among those low in initial Zika misperceptions compared to the *CDC-only* response ($b = .17$, $SE = .08$, $p = .03$), whereas it had no effect among those uncertain about Zika ($b = .02$, $SE = .06$, $p = .67$) or those high in initial Zika misperceptions ($b = −.12$, $SE = .08$, $p = .13$), although once again the trend suggested that the corrections are more successful among those higher in initial misperceptions compared to those lower.

However, when we examine the moderating role of initial misperceptions toward Zika on perceptions of the credibility of the source of the corrective information, we found no effects. Not only is there no direct impact of correcting misinformation on the credibility of the CDC or the trustworthiness of people who correct misinformation on Twitter (as described above) but also these relationships are not conditioned by preexisting misperceptions about Zika (*p*s > .14).[6]

Finally, we perform descriptive analysis to provide some additional context to our findings. In Table 2, we report participants' posttest beliefs regarding Zika as "correct," "neutral" or "incorrect," depending on their initial beliefs and the experimental condition. These results largely validate the regression model reported in Figure 2. Namely, every experimental manipulation appears to reduce misperceptions among those who initially held incorrect attitudes, while among neutral participants, there also appears to be

Table 2. Conditional Effect on Posttest Zika Misperceptions of Correction Type and Initial Levels of Zika Misperceptions.

		Experimental condition				
Initial belief	Posttest belief	Control (%)	User correction (%)	CDC correction (%)	User + CDC correction (%)	CDC + User correction (%)
Correct	Correct	83.6	75.0	79.0	76.2	68.9
	Neutral	16.4	15.2	15.3	19.7	22.7
	Incorrect	0	9.8	5.6	4.1	8.3
Neutral	Correct	12.0	19.2	23.1	28.7	23.1
	Neutral	82.7	71.7	65.8	64.8	65.3
	Incorrect	5.3	9.2	11.1	6.5	11.6
Incorrect	Correct	4.8	25.4	20.3	23.9	32.4
	Neutral	28.6	23.8	40.7	37.3	20.6
	Incorrect	66.7	50.8	39.0	38.8	47.1

Note. CDC = Centers for Disease Control and Prevention. Correct beliefs are defined as an average value on the Zika attitudes index between 1-3.99, Neutral beliefs are defined as an average of 4, and Incorrect beliefs are defined as an average value between 4.01-7.

moderate reduction in misperceptions. However, among those who initially held correct attitudes, both the *user* correction and the *CDC plus user* correction appear to potentially *create* misperceptions.

Discussion

Social media is increasingly part of the media landscape, which brings both risks and opportunities. Concerns about false information surrounding scientific and health issues are especially important: The lack of established gatekeepers can enable the spread of misinformation (Bessi et al., 2015; Sharma et al., 2017), but this study suggests that social media also offers a space for what we term *observational correction*, which occurs when social media users update their own attitudes after witnessing another user being corrected.

We find that a single correction from a reputable source like the CDC was sufficient to reduce misperceptions about the causes of the spread of the Zika virus that can be created when users are posting misinformation on the topic. Adding a correction from the CDC after another user has refuted the information—even with a link to the same content that the user posted—again enhances corrective effects.

Moreover, the credibility of the CDC was not harmed—but neither was it improved—when it engaged in this type of corrective action. This may suggest that the public views such behaviors as appropriate for the CDC, creating opportunities for scientific and health organizations to engage with the public. However, future research should directly examine different dimensions of credibility, such as expertise, trustworthiness, authority, or appropriateness (Amazeen et al., 2016; Eastin, 2001). Given the high levels of credibility that the CDC currently enjoys (Pew Research Center, 2015b), the organization should consider being more proactive in addressing misinformation as it arises on social media. Although previous research suggests that the CDC frequently interacted with the public as the Zika virus emerged as an issue of public concern—one study found that 39% of its tweets were replies to other users (Stefanidis et al., 2017)—it does not appear that it has been monitoring social media for misinformation but only responding to direct inquiries from other users. This opens up a potential avenue for the CDC to broaden its effectiveness in serving the public on issues of collective concern and to move beyond a one-way paradigm of science communication into interaction and dialogue with the public (Davies, 2008).

Conversely, a single user correction does not produce the same response. A single user was not able to reduce misperceptions on their own, nor did a user adding his or her rebuttal to an existing CDC correction further contribute to its effectiveness beyond the CDC. When a reputable organization has already corrected the misinformation, there is little value—and potentially some risk—from adding a second correction. Yet users are not exempt from responsibility: Previous research suggests that two corrections from users, when paired with links to expert sources, can reduce misperceptions on both Facebook and Twitter (Vraga & Bode, 2017). So users should weigh in when they see misinformation on social media, even if another user has already done so. And like the CDC, the trustworthiness of the people who comment on Twitter stories is not jeopardized by these corrective responses.

Our results also suggest that for three of the four types of correction, effects were stronger as compared to the control group among those who entered the study with higher misperceptions about the causes of the Zika outbreak. This is positive news, suggesting that correction is generally affecting those who need it most. Previous research suggests that contextual cues may inhibit the success of corrections based on preexisting beliefs (e.g., Garrett et al., 2013), reinforcing the importance of concise corrections on social media as explored in this study. Moreover, preexisting beliefs did not influence acceptance of the correction when it was offered by only the CDC; misperceptions declined for all individuals equally. This may suggest that the CDC is sufficiently persuasive that it affects everyone, and highlights its value as a corrective source. It also suggests that Zika remains an issue where the public is receptive to corrective information, reinforcing the value of these types of interactions online.

However, our results also suggest that having a social source adding a second correction after the CDC has already refuted the misinformation can produce backfire effects (e.g., Nyhan & Reifler, 2010; though see Wood & Porter, 2016). In this case, misperceptions are reinforced compared to the CDC-only condition among those who were initially *low* in misperceptions. Perhaps these participants become skeptical when they see repeated corrections with the same evidence. Future research should investigate under what circumstances multiple corrections induce backfire effects, as well as the psychological processes underlying the effects.

We believe that this study thus speaks to the power of *observational* correction on social media. In this study, we are not correcting the person who is posting the misinformation directly. Instead, our participants observe correction of misinformation that is posted on social media by unknown others. As such, it may avoid as strongly triggering the motivated reasoning processes that undermine efforts to correct misinformation (Lewandowsky et al., 2012; Nisbet et al., 2015; Nyhan & Reifler, 2010). Furthermore, it may be that the social fabric of platforms like Twitter or Facebook (Messing & Westwood, 2014) makes this type of observational correction easier than what occurs in other spaces, such as corrections within news articles. Future research should test whether such corrections remain effective when they are directed at known others or when they directly respond to an individual's post. Yet, even if such corrective efforts are ineffective or alienate the person being targeted with the correction, they may have merit in mitigating misperceptions among the broader social media community. Given heightened concerns with misinformation and "fake news" on social media (Pew Research Center, 2016; Sharma et al., 2017), testing the mechanisms for correcting societal misperceptions is critical.

Several limitations must be noted. First, this is an artificial Twitter feed, populated with content that users did not select. However, we do not think this compromises our findings. The average Twitter user follows 484 other accounts and the use of retweets and hashtags on Twitter creates more diverse communities (Papacharissi, 2012), so seeing tweets from organizations and users that the individual does not follow is likely common. Thus, we believe our manipulation is realistic. Research suggests that sanctions from high-status Twitter accounts can reduce racism in subsequent tweets (Munger, 2017); future research should examine how individuals respond if their own tweets are corrected by the CDC or another reputable organization.

Likewise, future research should also test whether social cues—such as the number of followers for an account or the number of "likes" for a correction—can enhance the effectiveness of corrective efforts (Munger, 2017). We suspect the CDC was effective in part because of its credibility (Pew Research Center, 2015b); if other users are seen as more credible because of account features or their own relationship to the poster, they may also be better able to correct misinformation than an unknown other user. Alternatively, other, less credible government or health agencies might be less effective in correction than what we find in this study.

Second, our sample of college students is less likely to be directly affected by Zika—they were both geographically removed from its spread and unlikely to be concerned about pregnancy (when Zika's effects are most devastating). As such, their resistance to corrective information is likely low, and participants may be susceptible to social desirability biases. Future research should test whether these mechanisms apply in more realistic situations and among populations who are more likely to be affected by Zika. Although the magnitude of the effect sizes seen here are relatively small, our descriptive analyses suggest they translate into on average a 20-percentage point reduction in people holding Zika misperceptions after seeing our corrections compared to the control condition, a meaningful difference. However, we cannot answer how long such corrections will persist, so findings should be treated with caution.

Overall, the conclusions are clear. Both users and organizations should speak up when they see misinformation on social media. For emerging social issues, reputable organizations like the CDC should monitor social media feeds and immediately attempt to rebut misinformation when it arises. Science communication on social media is too often one-way (N. M. Lee & Van Dyke, 2015), and these findings encourage an important opportunity for interaction and dialogue. Users can contribute to this effort by refuting misinformation and providing credible links (Vraga & Bode, 2017), although they should withhold their corrections once a reputable organization has corrected the misinformation. Even in this polarized media environment, correction makes a positive difference, without a cost to credibility. This is an important takeaway, as it should embolden institutions and users alike to engage in corrective action without concerns about negative implications for their reputation among those who see the correction.

Appendix

Example of stimulus material (CDC plus user correction).

Note. CDC = Centers for Disease Control and Prevention.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

Notes

1. We eliminated from our data set any participants who did not complete the survey, any second instances of a participant taking the survey, and any participants under the age of 18, per institutional review board requirements ($N = 349$). We do not include participants who failed an attention check (which occurred after the experimental manipulation, where participants were asked to select a particular response to a question embedded in a survey bank [$N = 320$]) in this analysis, but they are maintained in the provided data set.
2. Within the four experimental conditions, a second manipulation randomly assigned participants to either a consensus message ("The scientific consensus is there is no relationship between GMO mosquitoes and the spread of Zika") or discredit message ("This information has been discredited by world leaders in disease control and world health"). For the first two conditions with a single response, participants viewed one of these two messages. For the conditions with two responses, we varied whether the user or the CDC used the consensus versus discredit message. Future research will explore the effects of message type. We tested and found this factor did not interact with the analyses we describe and we control for this manipulation in all analyses. Please contact the lead author for details.
3. The Zika outbreak has resulted in the proliferation and spreading of multiple rumors, hoaxes, and statements of misinformation (Worth, 2016), and this one is among them (Griffiths, 2016; WHO, 2016). For information on the truth behind the Zika pandemic, see Al-Qahtani et al. (2016).
4. From the list provided at https://www.babycentre.co.uk/a1026121/gender-neutral-baby-names.
5. We define "correct" attitudes as an average score of 1.00 to 3.99 on the scale measuring Zika misperceptions, "neutral" attitudes as an average of 4, and "incorrect" attitudes as a score of 4.01 to 7.00, adopting a narrow definition of "neutral" beliefs. We recognize the range of ways to measure misperceptions: from Likert-style agreement scales as used here (see also Bode & Vraga, 2015; Nyhan & Reifler, 2010) to measures of probity from "false" to "true" (see Garrett et al., 2013; Thorson, 2016), or matching fact-checking organizations' categories (see Amazeen et al., 2016). Future research should explore whether measurement decisions influence our understanding of misperceptions and their correction.
6. For perceptions of CDC's credibility, there is no significant interaction between correction type and initial Zika misperceptions in all four conditions: the *user-only* correction ($b = -.21$, $SE = .14$, $p = .14$), the *CDC-only* correction ($b = -.05$, $SE = .15$, $p = .76$), the *CDC plus user* correction ($b = -.19$, $SE = .15$, $p = .19$), and the *user plus CDC* correction ($b = -.14$, $SE = .15$, $p = .34$). For perceptions of the trustworthiness of people who comment on news stories on Twitter, there is no significant interaction between correction type and initial Zika misperceptions for the *user-only* correction ($b = -.08$, $SE = .09$, $p = .33$), the *CDC-only* correction ($b = -.06$, $SE = .09$, $p = .53$), the *CDC plus user* correction ($b = -.04$, $SE = .09$, $p = .63$), and the *user plus CDC* correction ($b = -.10$, $SE = .09$, $p = .28$).

References

Aikin, K. J., Betts, K. R., O'Donoghue, A. C., Rupert, D. J., Lee, P. K., Amoozegar, J. B., & Southwell, B. G. (2015). Correction of overstatement and omission in direct-to-consumer prescription drug advertising. *Journal of Communication*, *65*, 596-618.

Aikin, K. J., Southwell, B. G., Paquin, R. S., Rupert, D. J., O'Donoghue, A. C., Betts, K. R., & Lee, P. K. (2017). Correction of misleading information in prescription drug television advertising: The roles of advertisement similarity and time delay. *Research in Social & Administrative Pharmacy*, *13*, 378-388.

Allgaier, J., Dunwoody, S., Brossard, D., Lo, Y. Y., & Peters, H. P. (2013). Journalism and social media as means of observing the contexts of science. *Bioscience*, *63*, 284-287. doi:10.1525/bio.2013.63.4.8

Al-Qahtani, A. A., Nazir, N., Al-Anazi, M. R., Rubino, S., & Al-Ahdal, M. N. (2016). Zika virus: A new pandemic threat. *Journal of Infection in Developing Countries*, *10*, 201-207.

Amazeen, M. A., Thorson, E., Muddiman, A., & Graves, L. (2016). Correcting political and consumer misperceptions: The effectiveness and effects of rating scale versus contextual correction formats. *Journalism & Mass Communication Quarterly*. Advance online publication. doi:10.1177/1077699016678186

Austin, E. W., & Dong, Q. (1994). Source v. content effects on judgments of news credibility. *Journalism Quarterly*, *71*, 973-983.

Bessi, A., Coletto, M., Davidescu, G. A., Scala, A., Caldarelli, G., & Quattrociocchi, W. (2015). Science vs. conspiracy: Collective narratives in the age of misinformation. *PLoS One*, *10*, e0118093.

Bode, L. (2016). Political news in the news feed: Learning politics from social media. *Mass Communication and Society*, *19*, 24-48.

Bode, L., & Vraga, E. K. (2015). In related news that was wrong: The correction of misinformation through related stories functionality in social media. *Journal of Communication*, *65*, 619-638.

Bravo, C. A., & Hoffman-Goetz, L. (2016). Tweeting about prostate and testicular cancers: Do Twitter conversations and the 2013 November Canada campaign objectives align? *Journal of Cancer Education*, *31*, 236-243.

Brossard, D. (2013). New media landscapes and the science information consumer. *Proceedings of the National Academy of Sciences of the United States of America*, *110*, 14096-14101.

Castillo, C., Mendoza, M., & Polete, B. (2011). Information credibility on twitter. In *WWW '11 Proceedings of the 20th international conference on world wide web* (pp. 675-684). New York, NY: ACM.

Centers for Disease Control and Prevention. (2016). *Key messages: Zika virus disease*. Retrieved from http://www.cdc.gov/zika/pdfs/zika-key-messages.pdf

Chaiken, S. (1980). Heuristic versus systematic information processing and the use of source versus message cues in persuasion. *Journal of Personality and Social Psychology*, *39*, 752-766.

Chaiken, S., & Maheswaran, D. (1994). Heuristic processing can bias systematic processing: Effects of source credibility, argument ambiguity, and task importance on attitude judgment. *Journal of Personality and Social Psychology*, *66*, 460-473.

Chen, X., Sin, S. J., Theng, Y., & Lee, C. S. (2015). Why students share misinformation on social media: Motivation, gender, and study-level differences. *The Journal of Academic Librarianship*, *41*, 583-592.

Choi, J. (2016). News internalizing and externalizing: The dimensions of news sharing on online social networking sites. *Journalism and Mass Communication Quarterly*, *93*, 816-835.

Chung, J. E. (2016). A smoking cessation campaign on Twitter: Understanding the use of Twitter and identifying major players in a health campaign. *Journal of Health Communication*, *21*, 517-526.

Dalrymple, K. E., Young, R., & Tully, M. (2016). "Facts, not fear": Negotiating uncertainty on social media during the 2014 Ebola crisis. *Science Communication*, *38*, 442-467. doi:10.1177/1075547016655546.

Davies, S. (2008). Constructing communication: Talking to scientists about talking to the public. *Science Communication*, *29*, 413-434. doi:10.1177/1075547008316222.

Diehl, T., Weeks, B. E., & gil de Zuniga, H. (2016). Political persuasion on social media: Tracing direct and indirect effects of news use and social interaction. *New Media & Society*, *18*, 1875-1895.

Dredze, M., Broniatowski, D. A., & Hilyard, K. M. (2016). Zika vaccine misconceptions: A social media analysis. *Vaccine*, *34*, 3441-3442.

Duke, J. C., Hansen, H., Kim, A. E., Curry, L., & Allen, J. (2014). The use of social media by state tobacco control programs to promote smoking cessation: A cross-sectional study. *Journal of Medical Internet Research*, *16*, e169.

Eastin, M. S. (2001). Credibility assessments of online health information: The effects of source expertise and knowledge of content. *Journal of Computer-Mediated Communication*, *6*. Retrieved from http://onlinelibrary.wiley.com/doi/10.1111/j.1083-6101.2001.tb00126.x/full

Ellison, N. B., Steinfield, C., & Lampe, C. (2007). The benefits of Facebook "friends:" Social capital and college students' use of online social network sites. *Journal of Computer-Mediated Communication*, *12*, 1143-1168.

Fischhoff, B. (2007). *Nonpersuasive communication about matters of greatest urgency: Climate change*. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.365.7934&rep=rep1&type=pdf

Fung, I. C., Fu, K., Chan, C., Sing, B., Chan, B., Cheung, C., . . . Tse, Z. T. (2016). Social media's initial reaction to information and misinformation on Ebola, August 2014: Facts and rumors. *Public Health Reports*, *131*, 461-473.

Garrett, R. K., Nisbet, E. C., & Lynch, E. K. (2013). Undermining the corrective effects of media-based political fact checking? The role of contextual cues and naïve theory. *Journal of Communication*, *63*, 617-637.

Giglietto, F., Iannelli, L., Rossi, L., & Valeriani, A. (2016). *Fakes, news and the election: A new taxonomy for the study of misleading information within the hybrid media system* (Convegno AssoComPol 2016, Urbino, 15-17 Dicembre 2016). Retrieved from https://ssrn.com/abstract=2878774

Griffiths, E. (2016). Was Zika outbreak caused by release of genetically modified mosquitoes in Brazil? *The Mirror*. Retrieved from http://www.mirror.co.uk/news/world-news/zika-outbreak-caused-release-genetically-7281671

Harris, J. K., Choucair, B., Maier, R. C., Jolani, N., & Bernhardt, J. M. (2014). Are public health organizations tweeting to the choir? Understanding local health department Twitter followership. *Journal of Medical Internet Research*, *16*(2), e31.

Hayes, A. F. (2013). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach*. New York, NY: Guilford Press.

Hermida, A., Fletcher, F., Korell, D., & Logan, D. (2012). Share, like, recommend: Decoding the social media news consumer. *Journalism Studies*, *13*, 815-824.

Himelboim, I., & Han, J. Y. (2014). Cancer talk on Twitter: Community structure and information sources in breast and prostate cancer social networks. *Journal of Health Communication*, *19*, 210-225.

Hovland, C. I., & Weiss, W. (1951). The influence of source credibility on communication effectiveness. *Public Opinion Quarterly*, *15*, 635-650.

Jerit, J., & Barabas, J. (2012). Partisan perceptual bias and the information environment. *Journal of Politics*, *74*, 672-684. doi:10.1017/S0022381612000187

Jong, W., & Dückers, M. L. (2016). Self-correcting mechanisms and echo-effects in social media: An analysis of the "gunman in the newsroom" crisis. *Computers in Human Behavior*, *59*, 334-341.

Kata, A. (2010). A postmodern Pandora's box: Anti-vaccination misinformation on the Internet. *Vaccine*, *28*, 1709-1716. doi:10.1016/j.vaccine.2009.12.022

Kim, G. (1967). The contribution of studies of source credibility to a theory of interpersonal trust in the communication process. *Psychological Bulletin*, *68*, 104-120.

Kotcher, J., Myers, T., Vraga, E. K., Stenhouse, N., & Maibach, E. (2017). Does engagement in advocacy hurt the credibility of scientists? Results from a randomized national survey experiment. *Environmental Communication*, *11*, 415-429.

Lee, C. S., & Ma, L. (2012). News sharing in social media: The effect of gratifications and prior experience. *Computers in Human Behavior*, *28*, 331-339.

Lee, N. M., & Van Dyke, M. S. (2015). Set it and forget it: The one-way use of social media by government agencies communicating science. *Science Communication*, *37*, 533-541. doi:10.1177/1075547015588600

Leiserowitz, A., Maibach, E., Roser-Renouf, C., & Hmielowski, J. (2012). *Global warming's six Americas in March 2012 and November 2011*. New Haven, CT: Yale Project on Climate Change Communication. Retrieved from http://climate-communication.yale.edu/publications/global-warmings-six-americas-in-march-2012-and-november-2011/

Lewandowsky, S., Ecker, U. K. H., Seifert, C. M., Schwarz, N., & Cook, J. (2012). Misinformation and its correction: Continued influence and successful debiasing. *Psychological Science in the Public Interest*, *13*, 106-131.

Messing, S., & Westwood, S. J. (2014). Selective exposure in the age of social media: Endorsements trump partisan source affiliation when selecting news online. *Communication Research*, *41*, 1042-1063.

Metzger, M. J. (2007). Making sense of credibility on the web: Models for evaluating online information and recommendations for future research. *Journal for the American Society for Information Science and Technology*, *58*, 2078-2091.

Metzger, M. J., Flanagin, A. J., & Medders, R. B. (2010). Social and heuristic approaches to credibility evaluation online. *Journal of Communication*, *60*, 413-439.

Munger, K. (2017). Tweetment effects on the tweeted: Experimentally reducing racist harassment. *Political Behavior*, *39*, 629-649. doi:10.1007/s11109-016-9373-5

National Science Board. (2016). *Science and technology: Public attitudes and understanding* (Science and Engineering Indicators 2016). Arlington, VA: National Science Foundation. Retrieved from https://www.nsf.gov/statistics/2016/nsb20161/uploads/1/nsb20161.pdf

Neiger, B. L., Thackeray, R., Burton, S. H., Giraud-Carrier, C. G., & Fagen, M. C. (2013). Evaluating social media's capacity to develop engaged audiences in health promotion settings: Use of Twitter metrics as a case study. *Health Promotion Practice*, *14*, 157-162.

Nelson, M. P., & Vucetich, J. A. (2009). On advocacy by environmental scientists: What, whether, why, and how. *Conservation Biology*, *23*, 1090-1101. doi:10.1111/j.1523-1739.2009.01250.x

Nisbet, E. C., Cooper, K. E., & Garrett, R. K. (2015). The partisan brain: How dissonant science messages lead conservatives and liberals to (dis) trust science. *ANNALS of the American Academy of Political and Social Science*, *658*, 36-66.

Nyhan, B., & Reifler, J. (2010). When corrections fail: The persistence of political misperceptions. *Political Behavior*, *32*, 303-330. doi:10.1007/s11109-010-9112-2

Oyeyemi, S. O., Gabarron, E., & Wynn, R. (2014). Ebola, Twitter, and misinformation: A dangerous combination? *British Medical Journal*, *349*, g6178.

Papacharissi, Z. (2012). Without you, I'm nothing: Performances of the self on Twitter. *International Journal of Communication*, *6*, 1989-2006.

Park, H., Rodgers, S., & Stemmle, J. (2013). Analyzing health organizations' use of Twitter for promoting health literacy. *Journal of Health Communication*, *18*, 410-425.

Peters, H. P., Dunwoody, S., Allgaier, J., Lo, Y. Y., & Brossard, D. (2014). Public communication of science 2.0. *EMBO Reports*, *15*, 749-753. doi:10.15252/embr.201438979

Peters, R. G., Covello, V. T., & McCallum, D. B. (1997). The determinants of trust and credibility in environmental risk communication: An empirical study. *Risk Analysis*, *17*, 43-54. doi:10.1111/j.1539-6924.1997.tb00842.x

Pew Research Center. (2011). *Health topics*. Retrieved from http://www.pewinternet.org/files/old-media/Files/Reports/2011/PIP_Health_Topics.pdf

Pew Research Center. (2013). *The role of news on Facebook: The Facebook news experience*. Retrieved from http://www.journalism.org/2013/10/24/the-facebook-news-experience/

Pew Research Center. (2015a). *How scientists engage the public*. Retrieved from http://www.pewinternet.org/2015/02/15/how-scientists-engage-public/

Pew Research Center. (2015b). *Most view the CDC favorably, VA's image slips*. Retrieved from http://www.people-press.org/2015/01/22/most-view-the-cdc-favorably-vas-image-slips/

Pew Research Center. (2015c). *Public and scientists' views on science and society*. Retrieved from http://www.pewinternet.org/2015/01/29/public-and-scientists-views-on-science-and-society/
Pew Research Center. (2016). *Many Americans believe fake news is sowing confusion*. Retrieved from http://www.journalism.org/2016/12/15/many-americans-believe-fake-news-is-sowing-confusion/
Sharma, M., Yadav, K., Yadav, N., & Ferdinand, K. C. (2017). Zika virus pandemic: Analysis of Facebook as a social media health information platform. *American Journal of Infection Control*, *45*, 301-302.
Southwell, B. G., & Thorson, E. A. (2015). The prevalence, consequence, and remedy of misinformation in mass media systems. *Journal of Communication*, *65*, 589-595.
Starbird, K., Maddock, J., Orand, M., Achterman, P., & Mason, R. M. (2014). Rumors, false flags, and digital vigilantes: Misinformation on Twitter after the 2013 Boston marathon bombing. In *iConference 2014 Proceedings* (pp. 654-662). Retrieved from https://www.ideals.illinois.edu/bitstream/handle/2142/47257/308_ready.pdf?sequence=2&isAllowed=y
Stefanidis, A., Vraga, E., Lamprianidis, G., Radzikowski, J., Delamater, P. L., Jacobsen, K. H., . . .Crooks, A. (2017). Zika in Twitter: Temporal variations of locations, actors, and concepts. *JMIR: Public Health Surveillance*, *3*(2), e22.
Thorson, E. (2016). Belief echoes: The persistent effects of corrected misinformation. *Political Communication*, *33*, 460-480.
Vraga, E. K., & Bode, L. (2017). I do not believe you: How providing a source corrects health misperceptions across social media platforms. *Information, Communication & Society*. Advance online publication. doi:10.1080/1369118X.2017.1313883
Vraga, E. K., Thorson, K., Kligler-Vilenchik, N., & Gee, E. (2015). How individual sensitivities to disagreement shape youth political expression on Facebook. *Computers in Human Behavior*, *45*, 281-289. doi:10.1016/j.chb.2014.12.025
Winter, S., Bruckner, C., & Kramer, N. C. (2015). They came, they liked, they commented: Social influence on Facebook news channels. *Cyberpsychology, Behavior, and Social Networking*, *18*, 431-436.
Winter, S., & Kramer, N. C. (2016). Who's right: The author or the audience? Effects of user comments and ratings on the perception of online science articles. *Communications*, *41*, 339-360. doi:10.1515/commun-2016-0008.
Wood, T., & Porter, E. (2016). *The elusive backfire effect: Mass attitudes' steadfast factual adherence*. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2819073
World Health Organization. (2016). *Dispelling rumours around Zika and complications*. Retrieved from http://www.who.int/emergencies/zika-virus/articles/rumours/en/
Worth, K. (2016, February). As Brazil confronts Zika, vaccine rumors shape perceptions. *Frontline*. Retrieved from http://www.pbs.org/wgbh/frontline/article/as-brazil-confronts-zika-vaccine-rumors-shape-perceptions/

Yeo, S. K., Cacciatore, M. A., Brossard, D., Scheufele, D. A., & Xenos, M. A. (2014, May). *Twitter as the social media of choice for sharing science*. Paper presented at the 13th International Public Communication of Science and Technology conference, Salvador, Brazil.

Author Biographies

Emily K. Vraga (PhD, University of Wisconsin) is an assistant professor in the Department of Communication at George Mason University. Her research focuses on how individuals process news and information about contentious political, scientific, and health issues, particularly in response to disagreeable messages they encounter in digital media environments. She is especially interested in testing methods to limit biased processing, to reduce misinformation, and to encourage attention to more diverse content online.

Leticia Bode (PhD, University of Wisconsin) is an assistant professor in the Communication, Culture, and Technology master's program at Georgetown University. Her work lies at the intersection of communication, technology, and political behavior, emphasizing the role communication and information technologies may play in the acquisition and use of political information.