Open Questions in Scientific Consensus Messaging Research

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Abstract

In recent years, there has been considerable interest in studying and using scientific consensus messaging strategies to influence public opinion. Researchers disagree, sometimes vociferously, about how to examine the potential influence of consensus messaging, debating one another publicly and privately. In this essay, we take a step back and focus on some of the important questions that scholars might consider when researching scientific consensus messaging. Hopefully, reflecting on these questions will help researchers better understand the reasons for the different points of debate and improve the work moving forward.

Introduction

In recent years, there has been considerable interest in studying and using consensus messaging strategies to address gaps between what the public believes and what science has shown. The general rationale for adopting such strategies for communicating about important societal problems such as the causes and consequences of global climate change is obvious. For decades, nefarious actors have cultivated a misleading narrative of continued scientific controversy on the existence of climate change, leading to public confusion and inaction¹ (see Brulle, 2014; Dunlap & McCright, 2010, 2011; Supran & Oreskes, 2017; Oreskes & Conway, 2010). It is only natural to want to set the record straight. After all, scientists *know* that anthropogenic climate change is underway and that it poses significant risks to human well-being. It also stands to reason that setting the record straight—communicating that the matter (at least from a certain altitude) has been settled within the scientific community—ought to close the so-called "consensus gap" (Cook, 2019; Pearce *et al.* 2017).

To what extent, though, does messaging about the scientific consensus surrounding an issue influence public opinion? The answer to this question is hotly debated. Some researchers stress that consensus messaging serves as a “gateway belief”, indirectly influencing public opinion and policy support by increasing public perceptions of scientific consensus (e.g., van der Linden, Leiserowitz, Feinberg, & Maibach, 2015). Yet this account has been challenged on a number of detailed fronts, including the appropriateness of the statistical methods used and the validity of the conclusions drawn (e.g., Kahan, 2017; also see the authors’ response, van der Linden, Leiserowitz, & Maibach, 2017). Other researchers do not challenge the Gateway Belief

¹ One example is the 2015 Heartland Institute-funded book *Why Scientists Disagree about Climate Change*, which was mailed to science teachers (including those at the college level) across the U.S. (Reid, Branch, & Newton, 2017).

Model (GBM), *per se*, but have not replicated the findings in studies aiming to extend the work (e.g., Cook & Lewandowsky, 2016; Deryugina & Shurchkov, 2016; Kerr & Wilson, 2018a; Landrum, Hallman, & Jamieson, 2019). Others still, have argued that the GBM underplays the impact of motivated reasoning, pointing out that partisan identity undermines consensus messages (Bolsen & Druckman, 2018), leading audiences to doubt the credibility of consensus messages (e.g., Pasek 2018), and sometimes messaging results in backfire effects (e.g., Cook & Lewandowsky, 2016; Ma, Dixon, & Hmielowski, 2019).

Our intent in this essay is not to referee these debates in detail. Instead, we propose to identify some foundational questions we believe scholars should consider when researching scientific consensus messaging. Hopefully, reflecting on these questions will help researchers better understand the reasons for the different points of debate—where we disagree and why—as well as improve the work moving forward.

Question 1: How should we approach and describe scientific consensus?

***The disagreement:** Many researchers have conceptualized consensus messaging as communicating descriptive norms (e.g., van der Linden, Clarke, & Maibach, 2015). These messages aim to correct misperceptions of consensus (false consensus) by highlighting the percent of scientists who agree with a proposition such as “climate change is real and human caused” or “genetically modified foods are safe for human consumption”. Other researchers point out that framing consensus as a descriptive norm (highlighting the number of scientists who agree) underplays a more important issue: the epistemic value of a consensus message is in the way consensus is actually formed. As John Cook phrased the objection: “our understanding of climate change is based on empirical measurements, not a show of hands” (2014). Even when expressing the state of scientific understanding, it is crucial that the messages are not worded in*

a way that could be confused for expressing scientists' opinions over the weight of evidence—even if the former follows from the latter.

What do we mean when we craft a message stating "there is scientific consensus that climate change is real and human-caused"? Do we mean that a majority of a voting body of relevant experts agree with that proposition? That nearly all of them do? That if you polled all scientists of a certain kind you'd get a certain level of agreement? That the peer-reviewed literature in a certain domain—or multimodal work across a number of domains—supports it (or presumes it)? On this range of approaches, consensus is seen as a matter of mere agreement.

Indeed, the GBM purports to use a descriptive norm—describing what others, themselves, think and do (*c.f.*, injunctive norms; Ravis & Sheeran, 2003; van der Linden, Clarke et al., 2015; also see Deutsch & Gerard, 1955)—to conceptualize scientific consensus, the percent of scientists who agree on a given issue. This “social norms approach” to changing people's attitudes and behaviors supposes that what individuals believe and do is based on misperceptions of what their social group members believe and do (Berkowitz, 2004, 2005). Therefore, interventions aiming to correct these misperceptions are expected to result in behavior change; and these interventions have been used in many health-related contexts, such as heavy drinking and smoking behaviors (Berkowitz, 2004). Indeed, similar concepts are integral for other influential communication and psychological theories, such as the theory of planned behavior (e.g., subjective norms; Ajzen, 1991).

In the original studies, van der Linden and colleagues use the message “97% of climate scientists have concluded that human-caused climate change is happening” (van der Linden *et al.* 2014; 2015) derived from Cook *et al.* (2013; see also Cook *et al.*, 2016; Anderegg, Prall, Harold, & Schneider, 2010; Doran & Zimmerman, 2009). Similarly, van der Linden and colleagues

evaluated consensus messages about vaccines, including the descriptive norm message, “90% of medical scientists agree that vaccines are safe,” and an injunctive or prescriptive norm message, “90% of medical scientists agree that all parents should be required to vaccinate their children” (van der Linden, Clarke *et al*, 2015). Other researchers also have used these numerical estimations of agreement when designing consensus messages to test. Dixon (2016), tested the GBM using the following message about genetically modified organisms, “A recent survey shows that 90% of scientists believe genetically modified foods are safe to eat.” These types of consensus messages contain two to three elements: a percentage of scientists who agree (e.g., 97%), (sometimes) a subclass of scientists (e.g., *climate* scientists), and the proposition presumably agreed upon by those scientists (e.g., that climate change is real and human caused).

Although van der Linden and colleagues have described these messages as descriptive norms meant to correct false consensus beliefs, there is a conspicuous difference between messages based on social norms generally and messages concerning scientific consensus in who the “others” are. In social norms work, the “others” are social partners or social group members (Berkowitz, 2004, 2005) whereas the GBM describes the attitudes of *experts*. Therefore, even without providing an explicit injunctive or prescriptive norm (e.g., telling people what they ought to do), the consensus message includes an *implicit* appeal to authority, and message creators presumably expect that the audience members will want to defer to those with expertise.

Yet research has demonstrated that authority commands like these can induce backfire effects (e.g., Conway & Schaller, 2005, see also Hart & Nisbet, 2012), and this approach relies on a mostly unified view among the public that scientists are credible. Although most people in the U.S. trust scientists generally, there are political divides in perceptions of certain domains of scientific experts and views of environmental researchers are particularly polarized (Pew

Research Center, 2019). It is also worth noting that credibility is mutable and context dependent (Landrum, Eaves, & Shafto, 2015). Communicating about publicly controversial topics can result in a reduction of a communicator's perceived credibility among certain subgroups (e.g., Dixon & Hubner, 2018; Landrum, Lull, Akin, Hasell, & Jamieson, 2017; Vraga, Myers, Kotcher, Beall, & Maibach, 2018).

Furthermore, including numerical estimates of agreement in a message also highlights that there is *some* disagreement. One might wonder, after all: "What do those 3% of apparently dissenting scientists say? What evidence do they have? Shouldn't we consider this as well?" Aklin and Urpelainen (2014) showed that when the public perceives even modest dissent among the scientific community, their support for environmental policy decreases. Presenting consensus as a proportion of agreeing scientists thus has the potential to play into what we call the *Galilean Gambit*: a David vs. Goliath story about how individual reason triumphed over (what we now all see as) the benighted dogma of the time. Climate denialists have been playing this card effectively for decades (Dunlap & McCright, 2011; Oreskes & Conway, 2010).²

Perhaps one way of avoiding such pitfalls is to highlight the distinction between consensus and mere agreement. Agreement can be achieved in many ways. That all members of a cult agree that their spaceship arrives tomorrow should not increase our credence that it will, given our background beliefs about how such agreement was likely formed. Agreement formed by more democratic or adversarial processes, by contrast, is often indicative of something beyond social cohesion (Miller, 2013). In the case of scientific consensus, that something is presumably the weight of the evidence for a given proposition. In this context, members of the

² Are they wrong to? Impure motivations aside, the answer is not as simple as one might initially suppose. Philosophers, historians, and sociologists of science have long debated the relative epistemic value of consensus and dissent (e.g., Mill 1859 / 1978; Longino 1990; Solomon 2001).

lay public could be seen as treating a robust scientific consensus — formed in particular ways (Beatty, 2017) — as evidence *that there is compelling scientific evidence* for a given claim.³

Consensus, in this sense, is evidence by proxy.

For instance, instead of using the 97% message, Bolsen and Druckman (2018) refer to a consensus conference⁴ and highlight the proposition that climate change is due to human activities:

A recent report, *Climate Change Impacts in the United States*, produced by 300 expert scientists and reviewed by the National Academy of Sciences as well as agencies with representatives from oil companies, puts much of the uncertainty to rest by stating that climate change ‘is primarily due to human activities.’

Similarly, Landrum and colleagues (2019) crafted a message that described the process of achieving consensus by conference with independent review (and publishing the consensus report) in the style of a press release:

A panel of 20 distinguished scientists convened by a non-partisan, scientific society, the National Academies of Sciences, Engineering, and Medicine, examined the use and impacts of genetically engineered food, often called GMOs, that are currently on the market.

The committee reviewed hundreds of scientific studies and gathered other relevant information through publicly held meetings and submission of information by outside parties, before writing a comprehensive report titled *Genetically Engineered Crops: Experiences and Prospects*.

Prior to its release to the public, the report underwent thorough independent review by another panel of scientific experts. With respect to human health, the report concluded that there is no substantiated evidence of a difference in risks to human health between GMOs and conventionally bred crops.

³ This richer construal of consensus, of course, depends for its epistemic significance on one’s background beliefs about the relevant processes and so may be less useful as a general messaging strategy than the descriptive norm approach, but it is important to distinguish between their expected function.

⁴ For more general philosophical discussion of the epistemology of consensus conferences, see Solomon (2007) and Stegenga (2016).

In this study, the message was presented with a meme-styled image that said “Scientific consensus is that GMOs are as safe to eat as conventionally bred crops” with an attribution to the National Academies of Sciences, Engineering and Medicine (see Landrum *et al.*, 2019).

Although these messages are longer, highlighting the *processes* by which consensus is formed offers those with a grasp of the relevant norms, values, and processes of science stronger epistemic support of the proposition in question.

Question 2: Under what conditions is consensus messaging considered successful?

***The disagreement:** Disagreements among researchers arise from different expectations of what it means to “find support” for the effects of consensus messages as well as what might undermine these effects. Some of these expectations, for example, seem to be based on differences in perspective on statistical methods, such as views about whether a total effect must be found prior to testing for mediation effects (Baron & Kenny, 1986, c.f., Hayes, 2009) and about the extent to which process models can give evidence of causality.*

Under what conditions should we regard an experiment on consensus messaging as successful? In the GBM, the presumed, ultimate goal of messaging about scientific consensus is to increase support for policies to address scientifically informed societal issues. To determine whether consensus messaging “works” in this practical sense, we could look for real-world effects. Kahan (2013a, 2013b) has argued, for example, that we can assume that consensus message campaigns do not work because the U.S. remains polarized over the existence, causes, and consequences of climate change (see Funk & Hefferon, 2019) despite more than a decade of messaging efforts by organizations such as the Consensus Project.

A reasonable counter to Kahan’s claim about the lack of real-world effects is that media echo chambers (e.g., Jasny, Waggle, & Fischer, 2015; Williams, McMurray, Kurz, & Lambert,

2015, van der Linden *et al.*, 2017) and variations in framing and coverage (e.g., Bolsen & Shapiro, 2017) limit exposure to such consensus information. This could be one reason that so few members of the public (including those who accept that anthropogenic climate change is occurring) provide a percentage greater than 90 when asked, in a survey, to estimate scientific consensus regarding global climate change (Cook, 2019, see also Deryugina & Shurchkov, 2016). Setting the real world aside, a minimum requirement for demonstrating potential efficacy would be favorable and replicable results in experiments, where exposure to a consensus message is controlled. However, researchers disagree about what constitutes favorable results.

A variety of tests are conducted to determine whether consensus messaging influences public attitudes and policy support. In some of the studies, the authors report results of pretest/posttest designs, comparing the change in the outcome variables for those who were exposed to the consensus message with participants who were assigned to a control task where presumably no pre/posttest change takes place (e.g., Kerr & Wilson, 2018b; van der Linden *et al.*, 2019). The majority of studies, however, conduct fully between-subjects designs (e.g., Bolsen & Druckman, 2018; Cook & Lewandowsky, 2016; Chinn, Lane, & Hart, 2018; Dixon, 2016; Deryugina & Shurchkov, 2016; Landrum *et al.*, 2019), examining the relationships between variables for those who were exposed to the consensus message versus those assigned to the control condition. This may be due, at least in part, to misinterpretations of the specifications of the GBM model. Though it is not obvious in the visualization of the model (Figure 1 in van der Linden, Leiserowitz, *et al.*, 2015), each of the variables involved in the GBM structural equation model are *difference* scores (e.g., the box labeled “Perceived Scientific Agreement” is actually the difference in perceived scientific agreement between pre-and post-exposure to the message).

A more obviously favorable result of exposure to consensus message campaigns would be direct and/or total experimental effects on people's climate-relevant attitudes and policy support.⁵ Arguably, if there was clear, consistent evidence of a direct effect where participants exposed to a consensus message report greater concern about climate change and greater support for climate change mitigation policies (outcome variables) than those exposed to a control message, this debate over the effectiveness of consensus messaging would not exist. Fuel for this debate likely comes from the following:

1. **Consensus Estimates:** Whether there is a significant relationship reported between exposure to a consensus message (vs control) and participants' estimates of scientific consensus may depend on the alignment between (a) the type of consensus message used (e.g., whether numerical estimates are provided) and (b) the way in which participants' estimates of scientific consensus are operationalized and measured;
2. **Attitudes and Policy Support:** Many researchers report finding no significant positive relationship between condition (exposure to the consensus message versus control) and the attitudes variables nor the policy support variable (Bolsen & Druckman, 2018; Chinn *et al.*, 2018; Cook & Lewandowsky, 2016; Deryugina & Shurchkov, 2016; Dixon, 2016; Kerr & Wilson, 2018b; Landrum *et al.*, 2019);

⁵ A few definitions for those less familiar with the jargon of mediation analysis: the *direct effect* (notated as *C-prime*) measures the extent to which changing the *independent variable* (X; e.g., exposure to a consensus message versus a control message) influences the *outcome variable* (Y; e.g., concern about climate change, support for mitigation policies) while holding the *mediator* (M; e.g., perceptions of scientific consensus) constant. The *indirect effect* (*AB*) measures changes in the outcome variable when X is held constant but the mediator changes as if X were manipulated. The *total effect* (*C*), then, is the *overall effect* of X on Y, or the sum of the direct and indirect effects (for linear models).

3. **Differential Responsiveness:** Different subgroups of individuals, such as those who vary on country of origin, worldviews, prior beliefs, political ideology, trust in science, and knowledge, are differentially responsive to consensus messages (Bolsen & Druckman, 2018; Chinn et al., 2018; Cook & Lewandowsky, 2016; Dixon, 2016; Landrum *et al.*, 2019); and
4. **Reactance:** Sometimes those different responses include reactance or boomerang effects (e.g., Cook & Lewandowsky, 2016; Deryugina & Shurchkov, 2016; van der Linden, Maibach, & Leiserowitz, *in press*⁶; Ma *et al.*, 2019) and negative outcomes on measurements of trust in science (e.g., Cook & Lewandowsky, 2016).

We explain each of these points in more detail below.

Evaluating if Exposure Influences Consensus Estimates (Point 1)

The effect most commonly tested for and found is the influence of the consensus message on participants' perceptions of scientific consensus. Typically, this involves exposing participants to a consensus message that provides the 97% value (or something similar) and later asking participants to estimate what percent of scientists agree on that issue (van der Linden *et al.*, 2015; see also, Dixon, 2016; Kerr & Wilson, 2018b; Myers *et al.*, 2015; van der Linden *et al.*, 2019). However, this association does not always replicate under different conditions.

Varying proportions. First, Chinn *et al.* (2018) show that varying the proportion of scientists who agree (with issues that are not politically or religiously charged) influences the relationship between exposure to a consensus message and estimates of scientific consensus (as

⁶ Although van der Linden et al (*in press*) state that they do not find evidence for reactance upon exposure to a consensus message, their data show Republicans and climate skeptics were more likely to perceive the consensus message as manipulative, which is consistent with reactance (p 6; see Dixon, Hmelowski, & Ma, *in press*)

well as other outcome variables). Exposure to messages communicating low levels of consensus (25%, 45%) corresponded to lower estimates of certainty than those exposed to a no consensus control. However, messages communicating a higher level of consensus (65%, 85%, 95%) did not differ significantly from the no consensus control (Chinn et al., 2018, p 813). Thus, the association between exposure to a consensus message (vs. a control message) and estimates of scientific consensus may be present or absent depending on the specific percentage used in the message.

Numbers vs. no numbers. Whether the consensus message contains a number (see Question 1) can also influence whether there is a relationship between exposure to a consensus message and estimates of scientific consensus. For example, Myers et al (2015) examined the potential influence of five different consensus messages that varied in the way they presented consensus (“97%...”, “97.5%...”, “97 out of 100...”, “More than 9 out of 10...”, and “an overwhelming majority...”). In the condition for which scientific consensus was described, but a number was not used (i.e., “an overwhelming majority of climate scientists have concluded...”), estimates of scientific consensus (and of certainty) did not differ significantly from the control condition (and were descriptively lower). Similarly, in Landrum *et al.*’s (2019) study described earlier, there was no significant relationship between exposure to the consensus message (which didn’t highlight a specific number of scientists in agreement) and participants’ estimates of the percent of scientists whom agree (Landrum *et al.*, 2019; see also Deryugina & Shurchkov, 2016). In fact, participants in both studies, Landrum *et al.* and Myers *et al.*, approximated on average that around 60% of scientists agreed. Landrum and colleagues also asked participants, who were not exposed to a consensus message, what percent of scientists would need to agree in order for

consensus to be achieved. There was wide variation in participants' responses, but the average was 62% (*Median* = 64.5, *SD* = 21.48).

This leaves open the question of what is really important for increasing policy support: recognizing that scientific consensus exists or estimates about the degree of agreement (Chinn et al., 2018; Aklin & Urpelainen, 2014; Johnson, 2017).

On this note, Myers and colleagues stated:

Our results suggest that qualitative statements may be ineffective; the one qualitative statement that we tested—which is similar to versions that are currently in use by prominent science-based organizations—had no impact relative to our control condition on enhancing public understanding of the scientific consensus. It may be that the ambiguity inherent in this type of verbal description of the level of scientific agreement leaves too much room for differing interpretations (2015, p. 8).

Alignment between message format and measurements of estimated consensus. It is possible, though, that the reason for the lack of significance for the relationship between exposure to a “soft” (e.g., Deryugina & Shurchkov, 2016), qualitative (e.g., Myers *et al.*, 2015), or process-based (e.g., Landrum *et al.*, 2019) consensus message and participants' estimates of scientific consensus is the lack of alignment between the message and the measurement. That is, when a non-numeric consensus message is used (which we argue is the way to proceed with future research in Question 1), participants' estimates of scientific consensus should not be captured using a 0% to 100% scale. Bolsen and Druckman (2018), for example, *did* find a significant relationship between exposure to a consensus message and estimates of scientific consensus using their process-based statement described earlier, but they asked participants

whether most scientists agree as opposed to asking them to estimate a specific percentage (also see Question 3).

Evaluating if Exposure Influences Attitudes or Policy Support (Point 2, Point 3)

In contrast to seeking effects on estimates of scientific consensus, direct or total effects for consensus treatment are rarely, if ever, found on attitudes and policy support variables when only between-subjects designs are conducted. Although van der Linden *et al.* (2019) report finding significant main effects on each of the dependent variables as part of a large-scale replication study with over 6,000 participants, these effects were based on testing the difference between the pre-/post-message exposure difference scores for the control condition compared to experimental condition. Other studies have measured only between-subjects effects, looking at the direct paths between the condition variable (exposure to consensus versus control) and the outcomes. In this sense, the large-scale replication also did not find significant relationships. The authors state in their paper: “For ease of interpretation, the direct paths between experimental assignment and all other variables in the model are not visually depicted and non-significant (all p s > 0.11)” (van der Linden *et al.*, 2019, p. 52). In personal communication, the first author of the study states that this is because the effects are fully mediated: “in the SEM, policy is predicted by many variables, including worry and attitudes, once you control for worry and attitudes, consensus condition is no longer significant (fully mediated) as predicted” (S. van der Linden, personal communication, March 28, 2020). Indeed, the authors of the GBM argue that finding direct or total effects of the consensus treatment on attitudes and policy support variables is not their intent. Instead, the authors focus on the significant *indirect* effects: Exposure to a consensus message (compared to a control message) increases the differences between participants’ pre- and post-message estimates of the percentage of scientists whom agree, which is presumed, then,

to influence the differences between pre- and post-message measurements of both attitudes and policy support.

One crucial disagreement relevant to this point, as highlighted above, is whether indirect effects ought to be examined in the absence of total effects. Although Baron and Kenny (1986) argued that they shouldn't, Hayes (2018) argues that "there is now a general consensus among methodologists that a total effect of X on Y should not be a prerequisite for searching for indirect effects" (p 117). To illustrate, Hayes describes a situation in which a total effect would net 0 (or close to it): when X exerts opposite influences on Y for different subgroups. This is very likely the case for scientific consensus messaging about climate change. A total effect near 0 is likely to be found should consensus messages about climate change exert opposite influences on Democrats compared to Republicans. Indeed, this seems likely given the strong predictive power of political ideology on climate change attitudes (Dunlap & McCright, 2008; Hamilton, 2011; Kahan, 2015; Kahan et al., 2012). However, the GBM does not include any individual difference variables (such as political ideology) as potential moderators in the path model.

Consensus messaging may not yield large direct effects on public attitudes. Indeed, not all methods of intervention yield large effects. Sometimes, interventions may only generate incremental change. This does not mean that the intervention is not worth pursuing; however, it does mean that researchers should take care not to overpromise.

Undermining Consensus Messages (Point 3, Point 4)

We may also ask what might *undermine* the effect of consensus messaging? Some researchers have pointed out that certain subgroups experience psychological reactance as a result of being exposed to consensus messages, which means those audiences can walk away from the messages more skeptical than they originally were. Indeed, several studies have found

evidence of reactance among certain subgroups upon exposure to consensus messages. Cook and Lewandowsky (2016), for example, found that U.S. participants who are strong supporters of unregulated free markets and were exposed to a consensus message reported lower estimates of the influence of human activity on climate change and lower trust in scientists than their counterparts in the control condition. Deryugina and Shurchkov (2016), too, found evidence of reactance. Skeptical participants who were randomly assigned to see the consensus message believed that scientists were less certain about climate change than those randomly assigned to the control group. The authors referred to this as “self-justification bias”.

Similarly, Ma, Dixon, and Hmielowski (2019) demonstrated that exposure to common consensus messages about climate change is associated with reactance among groups ideologically predisposed to reject climate change—namely, Republicans and climate skeptics. Although van der Linden and colleagues published an article in response to Ma *et al.*'s with the title “Exposure to Scientific Consensus Does Not Cause Psychological Reactance,” their data tell a different story. Indeed, Republicans and climate skeptics were more likely to perceive the consensus message as manipulative, a perception consistent with reactance (van der Linden *et al.*, *in press*; also see Dixon *et al.*, *in press*).

Reactance in response to consensus messages by certain subgroups does not necessarily invalidate the potential for consensus messaging to move public opinion. It just underlines a well understood truism of communication: different people respond to messages differently. It is important to ‘know your audience’ (see Besley & Dudo, 2019).

Question 3: When examining consensus messaging, which variables ought to be included and how might they be operationalized?

***The disagreement:** A final point of disagreement is what variables ought to be accounted for when modeling the influence of consensus messaging and how might these variables be operationalized. It is possible that the differences in operationalization can lead to differences in study outcomes. Moreover, it should go without saying that even if results are replicable, it doesn't automatically follow that they are valid or that they can be readily translated into practice. Thus, we ought to seriously consider how we measure the concepts of interest.*

As we have been discussing, the primary model used to explain how consensus messaging might influence public opinion and policy support is the Gateway Belief Model (GBM, van der Linden, Leiserowitz *et al.*, 2015). Conceptually, the GBM includes three sets of outcome variables: (1) pre/post-test differences in audience perceptions of scientific consensus (i.e., agreement among scientists), (2) pre/post-test differences in audience attitudes and beliefs about the issue, and (3) pre/post-test differences in audience support for policy or action. Studies have varied in the ways in which these variables have been operationalized. We argue that some operationalizations of these variables are more or less appropriate given what we understand scientific consensus to be (see Question 1) and what the goals of the message—and our studies—are.

Perceptions of scientific consensus

We do not disagree that the easiest target for correction via consensus message is public perception of scientific consensus. Yet, how do we operationalize perception of scientific consensus and pose it as a question to study participants? Whereas many large-scale public opinion surveys simply ask participants whether scientists agree or are divided on a given issue

(e.g., Pew Research Center, 2014), the authors of the GBM (and studies seeking to replicate or extend this model) often ask subjects to estimate the percent of scientists who agree on a 0% to 100% scale. As we suggested above (in the context of Question 1), highlighting the percent of scientists who agree may undermine the epistemic weight of a consensus argument by treating consensus as mere agreement. Moreover (as we discussed in the context of Question 2), the alignment between the type of consensus message used (e.g., numeric vs. non-numeric) and the measurement of participants' expectations of consensus might matter for whether the association is significant. Besides the binary item used by Pew Research Center and others, alternative options for posing this question include asking participants whether the majority of research studies (as opposed to scientists) support a proposition, or providing the claim that scientific consensus for a proposition exists (perhaps including some information regarding the context in which or process by which it was formed) and then asking participants to what degree they believe the claim is true or false.

Issue-relevant attitudes and beliefs

One point of contention in the evaluation of literature using the GBM is why some attitudes and beliefs variables are chosen to be used in the path model over others. For example, in the original GBM paper, van der Linden and colleagues include three mediating variables, two of which are specific to climate change: the belief that climate change is real and the belief that climate change is human caused. These two mediating variables are expected to influence the third mediating variable, worry about climate change. Unlike the other two variables, "worry" can be used in other contexts to represent risk perception of the issue at hand (e.g., GM foods, vaccines, medicinal cannabis).⁷ Notably, in the paper examining consensus messages in the

⁷ Though, worry is less appropriate for issues that do not directly involve risk perceptions, such as scientific consensus surrounding the explanatory power of the theory of evolution.

context of vaccination, van der Linden and colleagues asked two questions, one about perceptions of risks associated with vaccines (similar to the worry item) and one about whether people believe vaccines cause Autism. Yet, the authors only report a mediation model that uses the belief in the Autism–Vaccine link and not one that includes perceptions of risk⁸. So, which attitudes and beliefs variables ought to be considered when modeling the potential effects of consensus messaging? Must they be the same across different topics (e.g., vaccination, GM foods, climate change)? Does the model hold for some attitudes and belief variables but not others? What criteria, other than significant *p* values or model-fit statistics, should be used to determine which attitudes and beliefs are relevant and important to test and report?

In Kahan’s (2017) reanalysis of the GBM data, he also addresses some of the choices in operationalization made with respect to issue-relevant attitudes and beliefs. For example, Kahan argues that the item asking participants about the human-caused component of climate change assumes that people believe climate change is real, when at least 20% of the population rejects this premise. The question states, “Assuming climate change IS happening: how much of it do you believe is caused by human activities, natural changes in the environment, or some combination of both?” This item is then measured on a scale from 0 to 100, where 0 indicates the participant believes it is caused completely by natural changes and 100 indicates the participant believes it is caused completely by humans. If participants reject that climate change is real, did they simply not answer this question? If they didn’t answer, were they dropped from the study (i.e., listwise deletion), leading to a sample only composed of those who believe climate change is real? If they did choose an answer, are the results valid?

⁸ In personal communication with the first author, he states that the risk assessment item ought to have been included in the model for consistency but was left out due to debate with one of the paper reviewers (S. van der Linden, personal communication, March 28, 2020).

Similarly, Kahan criticized van der Linden *et al.*'s (2015) choice of measuring support for public action. Instead of proposing a specific type of policy that one might encounter on a ballot (e.g., reduce pollution by levying a fee on greenhouse gas emissions, Washington State Initiative 1631, which 80% voted against) or even asking about specific individual actions (e.g., donating a proportion of winnings, see Deryugina & Shurchkov, 2016), the van der Linden Leiserowitz *et al.* (2015) paper asked whether people should be doing more or less to reduce climate change. In this sense, the item may as well function as another attitude about climate change instead of a desire to do something about it. Future research ought to continue to test specific policy proposals (e.g., requiring electric companies to use renewable energy) or specific personal actions (e.g., plan to replace all lightbulbs with LEDs) to see whether communicating about the scientific consensus might indirectly increase specific public action (Ding et al., 2011; Goldberg et al., 2019).

Differential Responsiveness Variables

Notably missing from the GBM is the assumption that different audiences will interpret consensus messages differently. This seems like an oversight given evidence from decades of research on motivated reasoning (e.g., Kunda, 1990; Taber & Lodge, 2006); including variables to capture differential response may help to explain the frequent lack of total and direct effects in the GBM.

As highlighted by Druckman and McGrath (2019), receptivity to consensus messages could vary based on the underlying motivations of the audience. For example, individuals may have directional goals that lead them (perhaps subconsciously) to arrive at a specific conclusion that upholds their own viewpoints. To this end, participants who are exposed to a consensus message may engage in biased assimilation, interpreting the information in ways that allow them

to maintain their own beliefs (Lord, Ross, & Lepper, 1979). In addition, they could specifically seek out information that is likely to reinforce their beliefs (e.g., confirmation bias, Taber & Lodge, 2006), and they could avoid looking at or engaging with a consensus message if it is inconsistent with their views (e.g., selective exposure; Stroud, 2008).

On the other hand, participants could be motivated to form accurate conclusions, but still come to reject scientific consensus messages. One way of doing so would be to doubt the credibility of the source of the consensus message and/or the scientists featured in the message (Druckman & McGrath, 2019). For instance, in the study by Deryugina and Shurchkov (2016), 65% of participants who saw the consensus message doubted that it accurately represented the views of all scientists (also see Landrum *et al.*, 2019). Moreover, as previously stated, there are partisan differences in the perceived trustworthiness of environmental scientists (Pew Research Center, 2019). Political conservatives may doubt that consensus messages about climate change coming from liberal leaning organizations accurately reflect the state of scientific knowledge, especially when Conservative think tanks, like the Heartland Institute, sow doubt (see Pasek, 2018).

A New Model of Consensus Messaging

Thus, we propose that two more factors ought to be considered when examining how consensus messaging may influence public opinion and policy support. The first, we will call a differential responsiveness variable, borrowing and modifying the term from the differential susceptibility to media effects model (Valkenburg & Peter, 2013). For consensus messages about climate change, an obvious differential responsiveness variable would be political ideology. The second factor that we believe ought to be considered is perception of message credibility. In fact, we anticipate that the differential responsiveness variable will likely interact with message

characteristics to influence perceptions of message credibility (See Figure 1). With our collaborator, Joanna Huxster, we are currently testing our *Differential Responsiveness to Consensus Messaging Model* (DRCM2).

Figure 1. Differential Responsiveness to Consensus Messaging conceptual model. First, audiences are exposed to a consensus message. Second, audience members evaluate the credibility of the message based on the content of the message and their own social and dispositional characteristics. Third, if they find the message credible, audiences update their beliefs about the scientific consensus accordingly. Fourth, audiences' beliefs about the scientific consensus influence their attitudes about a topic (e.g., whether they are worried). Finally, their worry influences their support for relevant policies, conditional on their worldviews.

Conclusion

Strictly speaking, it cannot be taken for granted that the existence of a scientific consensus about a given proposition should, in itself, constitute a *prima facie* reason for a member of the lay public to accept that proposition (Solomon 2001; Miller, 2013; Beatty, 2017). But even if consensus is not epistemically significant *per se*, in certain circumstances it *can* serve as a useful pointer towards the truth—as evidence of evidence. This is because we can often correctly presume that in a scientific community characterized by certain institutional norms and processes — e.g., organized skepticism (Merton 1942), competition (Kuhn, 1962), and peer review — will be one in which a consensus *is* epistemically significant (Slater *et al.*, 2019). And if this cannot be presumed, it may be possible for members of the lay public to ascertain it

(Anderson, 2011). This, we submit, is a significant reason why communicating the scientific consensus on a given issue is often presumed to be valuable: it permits an epistemically defensible shortcut to describing what may be complex evidential considerations or establishing the expert credibility of individual scientists.

We — readers of this journal — can often accurately presume or ascertain whether the conditions or processes underlying consensus formation should incline us to see the truth of the agreed-upon proposition as the best explanation of the consensus. Despite eager reports of a “consensus on consensus messaging”, it remains, we contend, a still open question whether members of the lay public will respond to consensus messaging similarly or whether dispositional or cognitive differences will yield different responses.

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