[UNDER REVISED REVIEW AT ENVIRONMENTAL COMMUNICATION]

Open Questions in Scientific Consensus Messaging Research

Asheley R. Landrum (A.Landrum@ttu.edu)
College of Media & Communication
Texas Tech University
ORCiD: 0000-0002-3074-804X

Matthew H. Slater (mhs016@bucknell.edu)
Department of Philosophy
Bucknell University
ORCiD: 0000-0003-1982-2656

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 inaction[1] (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 *et al*., 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 *et al*., 2017). Other researchers do not challenge the Gateway Belief Model (GBM), *per se*, but have not replicated

[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).

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 resulting 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 describe scientific consensus?

The disagreement: *Many consensus messages used in the literature highlight a specific 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". Some researchers point out that framing consensus as a number of scientists who agree underplays a more important issue: 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 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 appears to conceptualize scientific consensus as the percent of scientists who agree on a given issue. 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) presumably 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 "90% of medical scientists agree that vaccines are safe" and "90% of medical scientists agree that all parents should be required to vaccinate their children" (van der Linden, Clarke, & Maibach, 2015). Other researchers, too, have used 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).

Arguably, the reason to incorporate a percent of scientists whom agree with a proposition is that it communicates relative certainty to the lay public simply. However, we should consider what else this might communicate. First, without explicitly being stated, the takeaway message from "97% of scientists *agree* that climate change is real and human caused," or from “90% of scientists believe genetically modified foods are safe to eat,” is that *you should believe like the scientists do*. But research has demonstrated that authority commands like these can induce backfire effects (e.g., Conway & Schaller, 2005, see also Hart & Nisbet, 2012). Second, it 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).

Framing consensus numerically 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 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 the (we now all see) benighted dogma of the time. Climate denialists have been playing this card effectively for decades (Dunlap & McCright, 2011; Oreskes & Conway, 2010).[2]

There are other ways of conceptualizing scientific consensus that deemphasize disagreement and focus the message on the weight of the evidence and/or on the norms and values of science. One such method is to highlight the process by which consensus was achieved. Instead of using the 97% message, Bolsen and Druckman (2018), for example, refer to a consensus conference (see Solomon, 2007; Stegenga, 2016) 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 (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.

[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).

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, they include reasons to trust the proposition, emphasizing the norms, values, and processes that make science trustworthy.

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 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 is consensus messaging 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) 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 is likely in part due to the fact that the GBM doesn't include pre-test measurements as part of the model's design, even if the GBM authors record and report these values in their manuscripts.

One potentially more obvious 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.[3] Arguably, if there was clear, replicable evidence of a direct effect

[3] 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

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 appears to 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**: There is rarely, if ever, a significant positive relationship reported between condition (exposure to the consensus message) 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; van der Linden et al., 2015, 2019);
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

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).

(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*[4]; 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 whom 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 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

[4] 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 actually 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*)

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 5 different consensus messages that varied in the way they presented the 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 actually 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*.'s and Myers *et al.*'s, 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. 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 significance of the change between pre- and post-exposure. 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 ps > 0.11)" (van der Linden *et al*., 2019, p. 52).

Importantly, however, 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 participants' estimates of the percentage of scientists that are in agreement, which is presumed, then, to influence 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 between X and Y. 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. Nor do the authors offer an explanation as to why they may not see significant direct or total effects.

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 over promise.

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 change 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 *et al.,* 2015). Conceptually, the GBM includes three sets of outcome variables: (1) audience perceptions of scientific consensus (i.e., agreement among scientists), (2) audience attitudes and beliefs about the issue, and (3) 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 use this model) often ask subjects to estimate the percent of scientists who agree on a 0% to 100% scale. As we argue for Question 1, highlighting the percent of scientists who agree may undermine the epistemic weight of a consensus argument by treating consensus as if it is achieved by vote. Moreover, as we discuss in 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 matters for whether the association is significant. Besides the binary item used by Pew Research Center and others, 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 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).[5] Notably, in the paper examining consensus messages in the 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 risk. 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

[5] 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.

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?

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), van der Linden's measure 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 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.

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), and 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 actually reflect the state of scientific knowledge, especially when Conservative think tanks, like the Heartland Institute, sew 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).

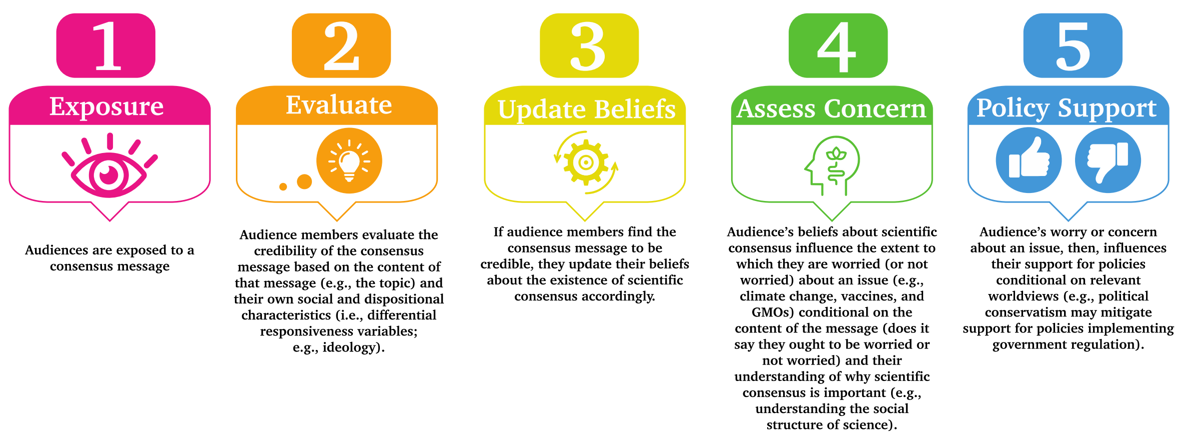

Figure 1. Differential Responsiveness to Consensus Messaging conceptual model. First, audiences are exposed to a consensus message. Second, audience members evaluate the credibility of the message based on the content of the message and their own social and dispositional characteristics. Third, if they 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. 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. 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.

References

Aklin, M., & Urpelainen, J. (2014). Perceptions of scientific dissent undermine public support for environmental policy. *Environmental Science & Policy, 38,* 173-177. doi: 10.1016/j.envsci.2013.10.006

Anderegg, W. R. L, Prall, J. W., Harold, J., & Schneider, S. H. (2010). Expert credibility in climate change, *PNAS*, *107*(27) 12107-12109. doi: 10.1073/pnas.1003187107

Anderson, E., (2011). Democracy, Public Policy, and Lay Assessments of Scientific Testimony. *Episteme*, *8*(2), 144–164. doi: 10.3366/epi.2011.0013

Baron, R. M. and Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology, 51*(6), 1173–1182. doi: 10.1037/0022-3514.51.6.1173.

Beatty, J., (2017). Consensus: Sometimes It Doesn't Add Up. In S. Gissis, E. Lamm and A. Shavit (eds.), *Landscapes of Collectivity in the Life Sciences*. Cambridge, MA: MIT Press, 179–199.

Besley, J. C., & Dudo, A. (16 April 2019). What it means to 'know your audience' when communicating about science. *The Conversation.* Retrieved from: http://theconversation.com/what-it-means-to-know-your-audience-when-communicating-about-science-111147

Brulle, R. J. (2014). Institutionalizing Delay: Foundation Funding and the Creation of U.S. Climate Change Counter-Movement Organizations. *Climatic Change 122*(4), 681–694. doi: 10.1007/s10584-013-1018-7

Bolsen, T., & Druckman, J. N. (2018). Do partisanship and politicization undermine the impact of a scientific consensus message about climate change? *Group Processes and Intergroup Relations*, *21*(3), 389-402. doi: 10.1177/1368430217737855

Bolsen, T., & Shapiro (2017). Strategic Framing and Persuasive Messaging to Influence Climate Change Perceptions and Decisions. *Oxford Encyclopedia of Climate Change Communication.* doi: 0.1093/acrefore/9780190228620.013.385

Chinn, S., Lane, D. S., & Hart, P. S. (2018). In consensus we trust? Persuasive effects of scientific consensus communication. *Public Understanding of Science, 27*(7), 807-823. doi: 10.1177/0963662518791094

Conway, L. G. III, & Schaller, M. (2005). When authorities' commands backfire: Attributions about consensus and effects on deviant decision making. *Journal of Personality and Social Psychology, 89*(3), 311-326. doi: 10.1037/0022-3514.89.3.311

Cook, J. (2019). Understanding and countering misinformation about climate change. In Chiluwa, I. & Samoilenko, S. (Eds.), *Handbook of Research on Deception, Fake News, and Misinformation Online* (pp. 281-306). Hershey, PA: IGI-Global.

Cook, J., & Lewandowsky, S. (2016). Rational Irrationality: Modeling Climate Change Belief Polarization Using Bayesian Networks. *Topics in Cognitive Science, 8*(1), 160–179. http://doi.org/10.1111/tops.12186

Cook, J., Nuccitelli, D., Green, S. A., Richardson, M., Winkler, B., Painting, R., Way, R., Jacobs, P., & Skuce, A. (2013). Quantifying the consensus on anthropogenic global warming in the scientific literature. *Environmental Research Letters, 8*(2), 031003. doi: 10.1088/1748-9326/8/2/024024

Cook, J., Oreskes, N., Doran, P., Anderegg, W. R. L., Verheggen, B., Maibach, E. W., Carlton, J. S., Lewandowsky, S., Skuce, A. G., Green, S. A., Nuccitelli, D., Jacobs, P., Richardson, M., Winkler, B., Painting, R., & Rice, K. (2016). Consensus on consensus: a synthesis of consensus estimates on human-caused global warming. *Environmental Research Letters, 11*(4), 048002. doi: 10.1088/1748-9326/11/4/048002/

Cook, J. (23 May 2013). On the value of consensus in climate change communication. *Skeptical Science*. Retrieved from: https://skepticalscience.com/value-consensus-climate-communication.html

Cook, J. (20 November 2014). Why we need to talk about the scientific consensus on climate change. *The Guardian.* Retrieved from: https://www.theguardian.com/environment/climate-consensus-97-per-cent/2014/nov/20/why-we-need-to-talk-about-scientific-consensus-on-climate-change

Deryugina, T., & Shurchkov, O. (2016). The effect of information provision on public consensus about climate change. PLoS ONE, 11(4), 1 –14. doi: 10.1371/journal.pone.0151469

Dixon, G. (2016). Applying the Gateway Belief Model to Genetically Modified Food Perceptions: New Insights and Additional Questions. *Journal of Communication, 66*, 888-908. doi: 10.1111/jcom.12260

Dixon, G., Hmielowski, J. & Ma, Y. (*in press*). More Evidence of Psychological Reactance to Consensus Messaging: A Response to van der Linden, Maibach, and Leiserowitz (2019). Environmental Communication. 10.1080/17524032.2019.1671472

Dixon, G., & Hubner, A. (2018). Neutralizing the effect of political worldviews by communicating scientific agreement: A thought-listing study. *Science Communication*, *40*(3), 393-415. 10.1177/1075547018769907

Doran, P. T., & Zimmerman, M. K. (2009). Examining the scientific consensus on climate change. EOS, 90(3), 22-23. doi: 10.1029/2009EO030002

Druckman, J., N., & McGrath, M. C. (2019). The evidence for motivated reasoning in climate change preference formation. *Nature Climate Change, 9,* 111-119. doi: 10.1038/s4158-018-0360-1

Dunlap, R. E., & McCright, A. M. (2008). A Widening Gap: Republican and Democratic Views on Climate Change. *Environment: Science and Policy for Sustainable Development, 50*(5), 26-35. doi: 10.3200/ENVT.50.5.26-35

Dunlap, R. E., & McCright, A. M. (2010). Climate Change Denial: Sources, Actors and Strategies. In C. Lever-Tracy (ed.), *Routledge Handbook of Climate Change and Society*. London: Routledge.

Dunlap, R. E., & McCright, A. M. (2011). Organized Climate Change Denial. In J. S. Dryzek, R. B. Norgaard and D. Schlosberg (eds.), *The Oxford Handbook of Climate Change and Society.* Oxford: Oxford University Press.

Funk, C., & Hefferon, M. (25 November 2019). U.S. Public Views on Climate and Energy. *Pew Research Center: Science and Society.* Retrieved from: https://www.pewresearch.org/science/2019/11/25/u-s-public-views-on-climate-and-energy/

Hamilton, L. C. (2011). Education, politics, and opinions about climate change: Evidence for interaction effects. *Climatic Change, 104*(2), 231-242. https://doi-org/10.1007/s10584-010-9957-8

Hart, P. S., & Nisbet, E. (2012). Boomerang Effects in Science Communication: How Motivated Reasoning and Identity Cues Amplify Opinion Polarization About Climate Mitigation Policies. *Communication Research, 39*(6), 701-723. doi: 10.1177/0093650211416646

Hayes, A. F. (2009). Beyond Baron and Kenny: Statistical Mediation Analysis in the New Millennium. *Communication Monographs 76*(4), pp. 408–420. doi: 10.1080/03637750903310360.

Jasny, L., Waggle, J., & Fischer, D. R. (2015). An empirical examination of echo chambers in US climate policy networks. *Nature Climate Change*, *5*, 782-786. doi: 10.1038/nclimate2666

Johnson, B. B. (2017). “Counting votes” in public responses to scientific disputes. *Public Understanding of Science, 27*(5), 594-610. doi:10.1177/0963662517706451

Kahan, D. M. (2013a). Annual "new study" finds 97% of climate scientists believe in man-made climate change; public consensus sure to follow once news gets out. Retrieved from: http://www.culturalcognition.net/blog/2013/5/17/annual-new-study-finds-97-of-climate-scientists-believe-in-m.html

Kahan, D. M. (2013b). Kahan on Cook et al.: 4 points. Retrieved from: http://www.culturalcognition.net/kahan-on-cook-et-al-4-points/

Kahan, D. M. (2015). Climate-Science Communication and the Measurement Problem. *Political Psychology, 36*(S1), 1-43. doi: 10.1111/pops.12244

Kahan, D. M. (2017). The “Gateway Belief” Illusion: reanalyzing the results of a scientific-consensus message study. *Journal of Science Communication, 16*(05) A03. doi: 10.22323/2.16050203

Kahan, D. M., Landrum, A. R., Carpenter, K., Helft, L., & Jamieson, K, H. (2017). Science Curiosity and Political Information Processing. *Advances in Political Psychology, 38*(S1), 179-199. doi: 10.1111/pops.12396

Kahan, D. M., Peters, E., Wittlin, M., Slovic, P., Ouellette, L. L., Braman, D., & Mandel, G. (2012). The polarizing impact of science literacy and numeracy on perceived climate change risks. *Nature Climate Change, 2,* 732-735. https://doi-org/10.1038/nclimate1547

Kerr, J. R., & Wilson, M. S. (2018a). Perceptions of scientific consensus do not predict later beliefs about the reality of climate change: A test of the gateway belief model using cross-lagged panel analysis. *Environmental Psychology, 59*, 107-110. doi: 10.1016/j.jenvp.2018.08.012

Kerr, J. R., & Wilson, M. S. (2018b). Changes in perceived scientific consensus shift beliefs about climate change and GM food safety. *PLoS One, 13*(7): e0200295. doi: 10.1371/journal.pone.0200295

Kunda, Z. (1990). The Case for Motivated Reasoning. *Psychological Bulletin, 108*(3), 480–498. doi: 10.1037/0033-2909.108.3.480

Kuhn, T. (1962) T*he Structure of Scientific Revolutions.* Chicago: University of Chicago Press.

Landrum, A. R., Eaves, B. S., Jr., & Shafto, P. (2015). Learning to trust and trusting to learn: A theoretical framework. *Trends in Cognitive Sciences*, *19*(3), 109-111. doi: 10.1016/j.tics.2014.12.007

Landrum, A. R., Hallman, W. K., & Jamieson, K. H. (2019). Examining the Impact of Expert Voices: Communicating the Scientific Consensus on Genetically-Modified Organisms. *Environmental Communication 13*(1), 51–70. doi: 10.1080/17524032.2018.1502201

Landrum, A. R., Lull, R. B., Akin, H., Hasell, A., & Jamieson, K. H. (2017). Processing the Papal Encyclical Through Peceptual Filters: Pope Francis, identity-protective cognition, and climate change concern. *Cognition, 166*, 1-12. doi: 10.1016/j.cognition.2017.05.015

Longino, H. (1990). *Science as Social Knowledge: Values and Objectivity in Scientific Inquiry*. Princeton: Princeton University Press.

Lord, C. G., Ross, L., & Lepper, M. R. (1979). Biased assimilation and attitude polarization: the effects of prior theories on subsequently considered evidence. J. *Personality and. Social Psychology, 37*(11), 2098-2109. Retrieved from: http://fbaum.unc.edu/teaching/articles/jpsp-1979-Lord-Ross-Lepper.pdf

Ma, Y., Dixon, G., and Hmielowski, J. D. (2019). Psychological Reactance From Reading Basic Facts on Climate Change: The Role of Prior Views and Political Identification. *Environmental Communication*, *13*(1), 71–86. doi:

Merton, R. K. (1942). The Normative Structure of Science. Reprinted in *The Sociology of Science: Theoretical and Empirical Investigations.* Chicago: University of Chicago Press.

Mill, J. S. (1859 / 1978) *On Liberty*. Indianapolis: Hackett.

Miller, B. (2013). When is Consensus Knowledge Based? Distinguishing Shared Knowledge From Mere Agreement. *Synthese*, 190, 1293–1316. doi: 10.1007/s11229-012-0225-5

Myers, T. A., Maibach, E., Peters E., & Leiserowitz, A. (2015). Simple Messages Help Set the Record Straight about Scientific Agreement on Human-Caused Climate Change: The Results of Two Experiments. *PLoS One*, *10*(7): e0133103. doi: 10.1371/journal.pone.0133103

Oreskes, N., and Conway, E. M. (2010) *Merchants of Doubt*. New York: Bloomsbury Press.

Pasek, J. (2018). It's not my consensus: Motivated reasoning and the sources of scientific illiteracy. *Public Understanding of Science*, *27*(7), 787-806. doi: 10.1177/0963662517733681

Pearce, W., Grundmann, R., Hulme, M., Raman, S., Kershaw, E. H., and Tsouvalis, J. (2017). Beyond Counting Climate Consensus. *Environmental Communication*, *11*(6), 723–730. doi: 10.1080/17524032.2017.1333965

Pew Research Center (August 2019). *Trust and Mistrust in Americans' Views of Scientific Experts*. Retrieved from: https://www.pewresearch.org/science/wp-content/uploads/sites/16/2019/08/PS_08.02.19_trust.in_.scientists_FULLREPORT_8.5.19.pdf

Pew Research Center. (2014). General public science survey final questionnaire August 15-25, 2014.

Reid, A., Branch, G., & Newton, S. (12 April 2017). Is no place safe? Climate change denialists seek to sway science teachers. *Union of Concerned Scientists Blog.* Retrieved from: https://blog.ucsusa.org/guest-commentary/is-no-place-safe-climate-change-denialists-seek-to-sway-science-teachers

Solomon, M. (2001). *Social Empiricism*. Cambridge: MIT Press.

Solomon, M. (2007). "The Social Epistemology of NIH Consensus Conferences". H. Kincaid and J. McKitrick (eds.) *Establishing Medical Reality*. Dordrecht: Springer, pp. 167–177.

Supran, G., & Oreskes, N. (2017). Assessing ExxonMobil's Climate Change Communications (1977-2014). *Environmental Research Letters*, *12*(8), 084019. doi: 10.1088/1748-9326/aa815f/pdf

Stegenga, J. (2016). Three criteria for consensus conferences. *Foundations of Science, 21*(1), 35-49. doi: 10.1007/s10699-014-9374-y

Stroud, N. (2008). Media Use and Political Predispositions: Revisiting the concept of selective exposure. *Political Behavior, 30*(3), 341-366. doi: 0.1007/s11109-007-9050-9.

Taber, C. S. & Lodge, M. (2006). Motivated skepticism in the evaluation of political beliefs. *American Journal of Political Science*, *50*(3), 755-769. doi: 10.1111/j.1540-5907.2006.00214.x

Valkenburg, P. M., & Peter, J. (2013). The differential susceptibility to media effects model. *Journal of Communication*, *63*(2), 221-243. doi: 10.1111/jcom.12024

van der Linden, S. L., Clarke, C. E., & Maibach, E. W. (2015). Highlighting consensus among medical scientists increases public support for vaccines: evidence from a randomized experiment. *BMC Public Health*, *15*, 1207. 10.1186/s12889-015-2541-4

van der Linden, S. L., Leiserowitz, A., Feinberg, G. D., & Maibach, E. W. (2014). How to communicate the scientific consensus on climate change: plain facts, pie charts or metaphors? *Climatic Change*, *126*(1-2), 255-262. doi: 10.1007/s10584-014-1190-4

van der Linden, S. L., Leiserowitz, A., Feinberg, G. D., & Maibach, E. W. (2015). The Scientific Consensus on Climate Change as a Gateway Belief: Experimental Evidence. *PLoS One* 10 (2):e0118489.

van der Linden, S. L., Leiserowitz, A., & Maibach, E. (2017). Gateway illusion or cultural cognition confusion? *Journal of Science Communication*, *16*(05) A04. doi: 10.2139/ssrn.3094256 van der Linden, S. L., Maibach, E., & Leiserowitz, A. (*in press*). Exposure to Scientific Consensus Does Not Cause Psychological Reactance. *Environmental Communication.* doi: 10.1080/17524032.2019.1617763

Vraga, E., Myers, T., Kotcher, J., Beall, L., & Maibach, E. (2018). Scientific risk communication about controversial issues influences public perceptions of scientists' political orientations and credibility. *Royal Society Open Science, 5*, 170505. doi: 10.1098/rsos.170505

Weisberg, D. S., Landrum, A. R., Metz, S. E., Weisberg, M. (2018). No Missing Link: Knowledge predicts acceptance of evolution in the United States. *BioScience*, 68(3), 212-222. doi: 10.1093/biosci/bix161

Williams, H. T. P., McMurray, J. R., Kurz, T., & Lambert, F. H. (2015). Network analysis reveals open forums and echo chambers in social media discussions of climate change. *Global Environmental Change, 32*, 126-138. doi: 0.1016/j.gloenvcha.2015.03.006