Public Reception of Climate Science: Coherence, Reliability, and Independence

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Wordcount: 6978

Abstract

Possible measures to mitigate climate change require global collective actions whose impacts will be felt by many, if not all. Implementing such actions requires successful communication of the reasons for them, and hence the underlying climate science, to a degree that far exceeds typical scientific issues which do not require large-scale societal response. Empirical studies have identified factors, such as the perceived level of consensus in scientific opinion and the perceived reliability of scientists, that can limit people’s trust in science communicators and subsequent acceptance of climate change claims. Little consideration has been given, however, to recent formal results within philosophy concerning the relationship between truth, the reliability of evidence sources, the coherence of multiple pieces of evidence/testimonies, and the impact of (non-)independence between sources of evidence. The current paper draws on these results to evaluate exactly what has (and, more importantly, has not yet) been established in the empirical literature about the factors that bias the public’s reception of scientific communications about climate change.

Keywords: testimony, consensus, source credibility, coherence, Bayesian inference,

Introduction

To what extent do scientists agree that human activity is changing the climate? This is a question that occupies a central position in current academic and policy debates about how to communicate climate change to the general public. Among mainstream scientific bodies (e.g., the national science academies of the world, the Intergovernmental Panel on Climate Change), there is no longer meaningful doubt that there is an anthropogenic influence on the climate (IPCC, 2013). Although scientists are strictly never ‘certain’ about anything, it is sometimes claimed[[1]](#footnote-1) that scientists are as certain about human activity and climate change as they are about the link between smoking and lung cancer. Even in the discourse of avowed climate change ‘sceptics’, there is comparatively little disagreement with this basic premise – the debate focuses primarily on *how much* of an impact human activity has (so-called ‘climate sensitivity’) and how problematic any changes will be (e.g., Capstick & Pidgeon, 2014).

However, awareness of the extremely high level of agreement among scientists is not widespread. In surveys of public opinion, participants routinely (and substantially) underestimate the level of consensus among climate scientists that climate change is happening (e.g., Leiserowitz et al., 2013; Lewandowsky et al., 2013; Poortinga et al., 2011; van der Linden, Leiserowitz, Feinberg, Maibach 2014) This trend is particularly pronounced in the US, with studies suggesting that as few as 42% of the population think most scientists are in agreement on the basic facts of global warming (Leiserowitz et al., 2013).

The underestimation of the scientific consensus has been repeatedly found to have attitudinal consequences: individuals who underestimate the level of consensus are likely to be less concerned about climate change and to indicate less support for policies to tackle climate change (Ding et al., 2012; McCright et al., 2013; van der Linden, Leiserowitz, Feinberg, & Maibach, 2015).

Misperceiving the scientific consensus on climate change is therefore important, as it is associated with lower levels of positive engagement with the question of how society should respond to climate change.

Several studies have, in response to this, sought to provide participants in experimental settings with information that seeks to correct their misperception of the consensus. In Lewandowsky et al. (2013), providing participants with the correct consensus information elevated average perceptions of the consensus and closed the gap between participants’ views and the ‘correct’ answer (although it did not eliminate the gap entirely – something which we will return to later).

Most notably, Lewandowsky et al. found that this effect occurred even for participants who exhibited higher levels of agreement with free market economic views (the single most consistent predictor of climate change scepticism). Lewandowsky et al.’s effect has been replicated in other studies, with US populations (also in an experimental context, e.g., van der Linden et al. (2015).

The conclusion that emphasising the extent of the consensus among climate change scientists is useful as a communications tool has therefore gathered support. In these studies (see also, Ding et al., 2012), participants are not discovering the degree of consensus for themselves (i.e., ‘first hand’) by reading journal articles for example. Rather, they are informed of the consensus by an information source (the experimenter in this instance). Beyond the scientists whose work comprises the consensus itself, the majority of the rest of us do not possess the relevant expertise to evaluate the scientific evidence (Collins & Evans, 2007). Consequently, this testimonial format is the way in which we receive our information about climate change. This has consequences for how such information affects our beliefs. Moreover, it *should* have consequences for how such information affects our beliefs. In this paper, we explore the normative issues that impact the reception of testimonial information about climate change; that is, we examine what can be said about the factors that influence how receptive a rational person *should* be to testimonial evidence.

A clearer understanding of this, we will argue, is of immediate relevance both to policy and to experimental psychological research seeking to understand lay people’s responses to consensus information. Recommendations to provide information about scientific consensus have not been received uncritically (see e.g., Cook & Jacobs, 2014, for a review). In particular, the ecological validity of experimental findings has been questioned on the grounds that communicating the consensus is precisely what many climate change communicators have been doing for almost two decades, to very mixed effect. Specifically, there is a consistent and reliable influence of political ideology (Kahan, 2012) and personal values (Corner et al., 2014) on perceptions of climate change. Attitudes on climate change have repeatedly been found to polarise along ideological lines (Kahan et al., 2012) and the same information about climate change is evaluated in opposing ways by people with sceptical and non-sceptical views about climate change --the well-documented ‘biased assimilation’ effect (see Corner et al., 2012).

Within research on climate opinion, the ‘cultural cognition’ hypothesis holds that people judge a piece of evidence to be reliable and credible to the extent that it fits with their ‘cultural worldview’ (a set of beliefs about how society ought to be organised and how risks ought to be managed – see Kahan, 2012). Messages about climate change may conflict with the worldview of individuals who endorse individualistic principles for societal organisation (because the solutions to climate change often involve regulating either individual freedom or businesses).

Because evidence about climate change is evaluated by different individuals according to their pre-existing ideological and value-based beliefs, there is no reason to expect ‘consensus information’ (still evidence, after all) to be any different (Corner & Roberts, 2014; Kahan et al., 2011). Different beliefs about climate change facts will influence people’s perceptions of the reliability of the consensus information: these beliefs are likely to be based both on a judgment of the reliability of the source providing the consensus information and the perceived reliability of the scientists themselves. Indeed, in the only study that has directly tested this, Kahan et al. (2011) presented one group of participants with a book excerpt communicating the consensus position that anthropogenic climate change is a clear risk based on well-founded scientific evidence, for example: “Scientific authorities at all major universities agree that the source of this [atmospheric CO2] increase is human industrial activity…” (p. 155). Participants with an egalitarian and communitarian worldview expressed greater faith in the book’s author through their agreement with the sentence “I believe the author is a trustworthy and knowledgable expert on global warming”, than did participants with a hierarchical and individualistic worldview – a pattern that was reversed when the excerpt suggested that the evidence for climate change was still equivocal.

As we shall demonstrate in the remainder of this paper, this role of source reliability is essential, complex, and interacts with other factors. The paper proceeds with a consideration of the formal aspects of testimony and the communication of consensus information, with the assumption that a better consideration of the factors that normatively comprise an effective argument will be beneficial in designing future appeals. Specifically, in the remainder we examine two aspects of testimonial evidence such as a report that “97% of climate scientists agree that humans are significantly raising global temperature” (Cook & Jacobs, 2014). We consider first the factors that influence how that report, considered as a piece of testimony, should be received, before examining the evidential value of the consensus itself and the factors that normatively govern it.

The complexity of testimony.

After years of neglect, testimony has become a key topic in epistemology (the philosophical study of knowledge), in keeping with the realization that much, if not most, of what we purport to know relies crucially on the testimony of others (e.g., Coady, 1994). Furthermore, epistemology itself has taken an increasingly formal turn, with a steady rise in the increase of Bayesian analyses as the basis for (putatively) normative analyses of how we should form reliable beliefs. This means that, arguably, epistemological research links more closely with research in other areas of cognitive science (in particular psychology and artificial intelligence) than ever before. Understanding of the factors that, normatively, should change people’s beliefs, and in what ways, has been substantially enhanced by this research. This section proceeds by taking some of the findings from the climate change literature mentioned above, and placing them in the context of a formal consideration of testimony. This sheds light on how climate science may better be communicated to the public.

Lewandowsky et al. (2013) reported that providing participants with the correct consensus information reduced the gap between their perceptions of this consensus and the ‘true’ (at least provided) figure, but did not reduce it entirely. This is an example of ‘conservative’ belief updating (e.g., Edwards, 1968; Phillips & Edwards, 1966; there is no political connotation to the term). This is a phenomenon that is not specific to climate change related issues. Rather, it is observed in such ‘dry’ contexts as the classic bookbag and poker chip experiments so popular with cognitive psychologists in the 1960s, in which participants are presented with repeated draws from bags containing coloured chips in varying proportions with the task of inferring the bag composition (for a recent review see e.g., Hahn & Harris, 2014). A number of possible explanations have been advanced for conservatism, including limitations in human information aggregation or failures to appreciate accurately the diagnosticity of evidence (see e.g., Edwards, 1968). However, for participants’ responses to information about degree of consensus on climate change, a rational alternative explanation for conservatism outlined in Corner, Harris and Hahn (2010) seems relevant. Corner et al. pointed out that in situations where information is received from a ‘source’ (i.e., it is not directly observed), one *should* typically not update one’s belief as much as if one had directly received the evidence oneself. It is very rare that one receives information from a source who can be considered completely infallible (i.e., 100% reliable). Consequently, the persuasiveness of information received via others will necessarily be diluted to some degree, as prescribed by a Bayesian analysis of source reliability (e.g., Corner et al., 2010; Hahn, Harris & Corner, 2009). The ‘conservative belief updating’ concerning consensus among climate scientists displayed by participants in Lewandowsky et al.’s (2013) study might thus well be evidence of rational belief updating in the light of information from a source that is seen as less than perfectly reliable.

Superficially, adjusting one’s belief less because a source is viewed as less than fully reliable (as in Kahan et al. 2011) may seem similar to ‘motivated reasoning’: One adjusts one’s perception of the reliability of the source, so as to maintain a preferred belief (for a review of motivated reasoning, see Kunda, 1990; for a recent critique see Hahn & Harris, 2014). It is important to note, however, that an infallible source is the exception rather than the rule, and even trustworthy sources make honest mistakes. This corresponds to Schum’s (1994) distinction between a witness’s veracity/objectivity and their sensitivity. A source high in veracity will faithfully report what they believe is the truth, whilst a source high in sensitivity will hold a belief that is close to the objective truth. Veracity and accuracy are independent of one another in that knowledgable sources can intentionally mislead, and this distinction between source trustworthiness (veracity/objectivity) and expertise (sensitivity) seems relevant also when considering how best to communicate scientific consensus information to people.

A consideration of source reliability also enables one to capture other results that have been taken to reflect motivated reasoning and that are widely considered to be irrational, in particular belief polarization. Belief polarization is the phenomenon whereby the same piece of information draws different (indeed, opposite) conclusions from different people. Such a result is frequently observed in response to climate change information (see e.g., Cook & Lewandowsky, this volume, and references therein; Corner et al., 2012). Jern, Chang and Kemp (2014, see also, Cook & Lewandowsky, this volume in a climate change context) show how rational agents, who update their beliefs normatively - in line with Bayes’ theorem- may change their beliefs in opposite directions, given the same piece of evidence, simply because they have different underlying causal models of the world. Of direct relevance to the current discussion, where evidence is received via testimony, the same piece of testimonial evidence (e.g., a newspaper report providing evidence on a topic) can have opposite effects if people have opposing views on the reliability of the source. If one thinks it more likely that what someone says on a topic will be false rather than true (perhaps because our belief in their trustworthiness is low), then hearing what they have to say should make us more convinced of the *opposite*. As the simulations of Olsson (2013) show, belief polarization may thus arise in groups of subjectively rational Bayesian agents, simply because they seek to estimate, on the basis of their present beliefs about the world, the reliability of the sources from whom they receive information (cf. Thagard & Findlay, 2010).

 Of course, we may feel that specific types of evidence should be required before we believe that someone’s testimony is probably negatively correlated with the truth. Arguably more common will be the case where we think others unreliable in the sense that what they say is simply uncorrelated with the truth or falsity of the issue at hand, in which case our beliefs will not (and should not) change in response to what it is they tell us. However, any less than fully reliable source transmitting evidence will (normatively!) reduce the evidential value, and hence impact, of that evidence (see e.g., Hahn et al., 2009; Friedman, 1987; Schum, 1981; Bovens & Hartmann, 2003) just as one can be less sure what was said by someone when receiving a report of what they said second- or third-hand in a game of Chinese whispers.

In the case of the Lewandowsky et al. (2013) example above, where a communication states “97% of climate experts agree…”, there are a number of reliability issues at play. Firstly, there is the reliability of the climate experts themselves, and secondly there is the reliability of the individual who is reporting that 97% of climate experts agree. Figure 1 shows a simple way to model this situation within the framework of Bayesian probability and, more specifically, Bayesian Belief Networks (for an introduction to Bayesian Belief Networks see e.g., Korb & Nicholson, 2003) that makes explicit that the reports of information sources can be affected by both their trustworthiness and their expertise. In this situation, the hypothesis under consideration is that it is indeed the case that ‘97% of experts agree.’ This hypothesis can be either true or false, and the source can report that it is either true or false. The relationship between the source’s report and the objective truth of the hypothesis is determined by the trustworthiness and expertise of the source.



*Figure 1*. Capturing a source’s expertise and trustworthiness within a Bayesian Network (see Hahn, Oaksford & Harris, 2013) where a source reports that a particular consensus level on anthropogenic climate change obtains. The hypothesis under consideration is the correctness of that.

As many readers will know, networks such as that in Figure 1 represent dependency relationships between variables and thus simplify normative, Bayesian computations. In other words, they simplify calculation of degrees of belief on observing a given piece of evidence for someone who assumes the relationships described in the network model. Specifically, the network in Fig. 1 allows calculation of a degree of belief in the proposition that ‘97% of experts agree’ having received a report to that effect. Such networks (like the Bayesian framework more generally) thus capture *consistency* requirements between beliefs in the sense that if we believe certain things about the world we should believe certain other things as well. Respecting these consistency requirements means that our beliefs are rational; and even though the normative requirements are about relationships between beliefs, and not about whether they are actually true or false, ‘being Bayesian’ (representing degrees of belief by probabilities and updating beliefs via Bayes theorem) suffices to minimize the inaccuracy of one’s beliefs about the world (see Leitgeb & Pettigrew, 2010; and on the wider issue of why the Bayesian framework may be taken to provide norms for beliefs and their revision, e.g., Corner & Hahn, 2013; Hahn, 2014).

The exact value of one’s degree of belief in the claim that ‘97% of experts agree’ upon hearing a report to that effect will depend on the exact probabilities (degrees of belief) assigned to the individual nodes and the conditional probabilities that govern their inter-relations. What matters for present purposes is not exact values, but the kinds of qualitative interactions between variables that arise. Bayesian networks aid conceptual analysis because even very simple models can make clear that non-intuitive consequences may follow from their simple premises. We have already mentioned one example of this above in the form of demonstrations that belief polarization and biased assimilation can arise in entirely rational Bayesian agents.

To begin to look at the consequences of the interdependencies outlined in networks such as that presented in Figure 1, we might take the basic considerations concerning expertise and trustworthiness just outlined to be reflected in conditional probabilities such as those shown in Table 2 (see Harris, Hahn, Hsu & Madsen, 2014). In other words, for expertise, we assume a genuine expert is highly likely to accurately report the evidence, whilst the report of a total non-expert (a maximally unreliable source) bears no systematic relationship with the evidence (as in Bovens & Hartmann, 2003; and Jarvstad & Hahn, 2011). Trustworthiness, on the other hand, captures the likelihood of the source being a systematic deceiver. Consequently, an expert who is trustworthy with respect to this issue will report the true value of the hypothesis, a non-trustworthy expert will report the opposite of this, and both trustworthy and non-trustworthy non-experts will report random values. Constructing a network such as this is useful in this context because it allows one to track not only how beliefs should change in light of evidence received, but to compare the impact of evidence across different scenarios.

Table 1. *Conditional probabilities for Trustworthiness and Expertise.*

|  |  |  |
| --- | --- | --- |
|  | 97% of experts agree = “TRUE” (H) | 97% of experts agree =”FALSE” (¬H) |
|  | TRUSTWORTHY (T) | NOT TRUSTWORTHY (¬T) | TRUSTWORTHY (T) | NOT TRUSTWORTHY (¬T) |
|  | EXPERT (E) | NOT EXPERT (¬E) | EXPERT (E) | NOT EXPERT (¬E) | EXPERT (E) | NOT EXPERT (¬E) | EXPERT (E) | NOT EXPERT (¬E) |
| REPORT =’YES’ | High | .5 | Low | .5 |  Low | .5 | High | .5 |
| REPORT = ‘NO’ | Low | .5 | High | .5 | High | .5 | Low | .5 |

*Note.* The values represent the conditional *P*(*Rep*) – where *P*(*Rep*) corresponds to a report of ‘yes’ and *P*(*¬Rep*) corresponds to a report of ‘no.’ Thus, for example, the value ‘High’ in the top-left cell of the table indicates that the probability *P*(*Rep*|*H,T,Exp*) is high.

In the context of communicating consensus information it is important to consider how the source reporting upon the 97% consensus has obtained her information. Figure 2 shows a situation in which the source providing the report has herself received a report from five climate experts (the five could be any number one likes, but space restrictions limit us to five in Figure 2). This report concerns the truth of the statement that fossil fuels cause global warming.



Fig. 2. A reporting source such as a newspaper reporter receiving 5 expert verdicts.

In other words, the network of Fig. 2 represents the case in which the information source (which might for example be a national newspaper, or an experimenter) receives information from climate experts and subsequently reports the percentage of climate experts who state that fossil fuels cause global warming. As can be seen from Table 2, if the source is perceived to be completely non-expert then it makes no difference how many scientists they say agree with the consensus. Similarly, given the relationship between trustworthiness and the report, if one is maximally unsure as to whether the source is attempting to deceive one or not, then the information will have no effect on one’s belief in the hypothesis. Once the prior on the trustworthiness of the source falls below .5, whatever is then reported leads to belief update in the opposite direction. Independent university scientists themselves may score high on perceived trustworthiness and expertise (Leviston & Walker, 2010, as cited in Lewandowsky et al., 2013), but perceived characteristics of the reporting source may render this irrelevant.

 However, what if we ourselves were to be the source directly receiving the scientists’ verdicts? What evidential value should we ascribe to the experts’ testimonies and the level of agreement they exhibit? There are several distinct sets of formal results in the literature that speak to this question.

The first of these is a long tradition of examining ‘voting paradigms’: in the first instance, we might simply take the experts’ verdict to be a ‘vote’ concerning a state of affairs in the world and ask ourselves how likely this is to indicate that what the majority says is actually true. Viewed as an argument for whether or not anthropogenic climate change is happening, pointing to a majority opinion within some group forms a so-called appeal to popular opinion: ‘most agree that *X*, therefore *X* is (likely to be) true’. Appeals to popular opinion have typically been viewed as fallacious (see Hahn & Oaksford, 2006) but there is, in fact, a sizeable body of research indicating that group verdicts can be remarkably accurate, and more accurate than the individuals within the group (see e.g., Clemen, 1989; Page, 2005; relevant research is also found under the header of ‘wisdom of the crowds’ Surowiecki, 2004). A classic result here is Condorcet’s (1785) jury theorem. Condorcet’s theorem shows that given two alternatives, of which only one is correct, such as the truth or falsity of a claim, a group verdict based on simple majority may not only outperform the individual judges in terms of accuracy, but as group size increases, will, in fact, converge on the truth.

Condorcet’s basic result assumes *n* voters whose choices are independent of one another, and a probability, *p*, that each voter will pick the correct alternative which is assumed to be the same for all voters. If that probability is greater than .5 (assuming prior odds for the alternatives that are even), then the probability that the group choice, *PN*, will be correct, will not only be higher than *p* (i.e. the group verdict will be more accurate than the individual voters), but it will increase rapidly with group size *N*, and will approach infallibility in the limit.

This is true regardless of how much the voters know, as long as they know something (if their accuracy is at chance, i.e. *p* = .5, then the group verdict too will remain equal to tossing an coin; and, of course, if they are systematically biased against the right option, i.e., *p* < .5, then the reverse holds: *PN* will be even lower, and converge to 0). So it is not required that the individual voters are very knowledgable or accurate. Their degree of competence merely affects how high the probability of a correct choice is for a group of given size, and how rapidly the asymptote of perfect knowledge is approached as group size increases.

There are two immediate aspects of interest from even this simple formal model: for one, it is likely to surprise people, and there seems room in public communication for information about the conditions under which group verdicts provide diagnostic information even where the group members are not particularly accurate. Second, it draws attention to the fact that ‘agreement’ can be viewed in different ways. In the studies discussed, participants cannot know whether there are 10, 100 or 1000 climate scientists underlying the ‘97%’ consensus.

There is a strong normative intuition that absolute numbers and not just percentages should be relevant to our confidence that the majority verdict is true. However, simple models as those discussed thus far also reveal this issue to be remarkably complex.

List (2004) shows that under the simple Condorcet model it is in fact *only* the size of the absolute margin of the majority that matters, not the proportion: 100 out of 110 is as good as 1000 to 1010. However, this aspect of the simple Condorcet model depends on whether or not the ‘jurors’ are as accurate in voting for a claim in the case that it is actually true as they are in voting against a claim in the case that it is false. Such equal accuracy for, what are in signal detection terms, ‘hits’ and ‘correct rejections’ (Green & Swets, 1968) seems unlikely in scientific contexts, such as climate change. Here, it may be considerably more difficult to find evidence for a hypothesis, given that it is true, than to find evidence that it is not, when it is false. Depending on which is harder, the same absolute margin (e.g., a difference of 10 votes) may be normatively more *or less* compelling when reflecting a large proportion than a small proportion.

However, all this in turn hinges on the fact that jurors in the basic paradigm are assumed to be *independent* --again, a condition often not met in the real world, yet one that is intuitively highly consequential. If all those expressing their view on climate change were to simply take their opinion from one opinion leader in the group, there is essentially only a single ‘vote’, and the fact of the consensus would be entirely irrelevant: the group verdict would be no more accurate than that single scientist. Needless to say, science is not like that: scientists’ careers hinge on them making unique, individual contributions. Publications, research funding and promotion depend on contributing novel evidence and/or theory, and scientists compete for these resources. But of course scientists are not wholly independent either: communication, education, common methods, peer review etc. result in non-independence across scientists. Such an intermediate degree of dependence is captured in the model of Fig. 3.



Fig. 3. A simple model of multiple reporting experts that includes not just their individual reliability but also the fact that they are not entirely independent due to the common framework (CF) in which they operate as scientists.

This simple model is used by Bovens and Hartmann (2003) to examine interactions between degree of dependence, reliability of the individual voters (here scientists), and how likely the majority verdict is to be correct.[[2]](#footnote-2) For one, the proportion of scientists expressing a particular view now matters even in the case where the chance that a scientist indicates that anthropogenic climate change is happening when in fact it is, is the same as the chance that she finds that it is not, when it is not. In other words, the mere fact that the scientists are no longer assumed to be wholly independent shifts the situation from one in which only the absolute margin of the majority opinion matters to one where the proportion of the majority matters as well. Second, the model shows subtle interactions between perceived reliability and degree of independence. Hearing multiple scientists agree should increase our belief in their reliability. Surprisingly, whether that increase will be greater in the case where they are independent than when they are not, however, depends on how reliable they are perceived to be and whether or not they are perceived to be biased toward a positive report or not.

 Importantly, the fact that scientists show some degree of dependence is (normatively) no bar to their agreement increasing our degree of belief in what it is they claim (see Bovens & Hartmann, 2003; and also in the context of the Condorcet framework, Ladha, 1992).

 Finally, all the same factors (and their interactions) are in play not just for individuals’ summary verdicts on whether or not anthropogenic climate change is happening, but also at the level of the evidence that goes in to those summary conclusions. Different pieces of evidence may *cohere* (or ‘hang together’) to a greater or lesser extent, whether in a courtroom (the suspect ‘had a German accent and was carrying a soccer ball’, vs. ‘had a German accent and was carrying a cricket bat’) or in a climate context (e.g., shrinking polar ice and increased incidences of heatwaves vs. shrinking polar ice and a series of particularly cold winters in North America)

 In fact, ‘consensus’ among scientists’ verdicts is just a particular type of coherence. In the more general case, coherent evidence is not always more likely to be true (Olsson, 2005, Bovens & Hartmann, 2003) though it often will be (Glass, 2007). Nor will it always be better to obtain evidence from independent sources (Bovens & Hartmann, 2003) though a group of scientists who individually produce pieces of evidence that as a whole cohere are more likely to be reliable than when the evidence is less coherent (see Olsson & Schubert, 2007; Schubert, 2012). In all of this, coherence, reliability and prior probabilities interact, and interact with independence.

 In summary, simple formal models such as those described here demonstrate that the effects of consensus/coherence, reliability of sources, prior expectations (i.e, prior probabilities) and independence/non-independence between sources can *normatively* hardly be evaluated in isolation.

 One may legitimately query how models as simple as the ones considered here can provide prescriptions for what should count as a rational response to evidence in a world that is far more complex. [[3]](#footnote-3) However, it seems extremely unlikely that increasing model complexity –to mirror the greater complexity of a real world scenario such climate change- will decrease the degree of interaction observed between these key factors. Thus we feel confident in asserting that the general factors of reliability, coherence and independence and their interaction are all of genuinely central importance in this context.

 At the same time, the simplicity of these models works in their favour if we consider them to provide indications of what might *descriptively* characterize human behaviour. First, in many real world circumstances, what we know about the world is limited, regardless of how complex the world might actually be. Simple models such as those described may reflect the best we can do and thus represent rather faithfully simplifying assumptions we are forced to make. For those who consider it a plausible assumption that human behaviour seeks to approximate, at least broadly, what would in fact be rational (see e.g., Anderson, 1990; and for a review Hahn, 2014), there is thus also some reason to believe that these models may capture some aspects of actual human behaviour. Even setting aside entirely any consideration of rationality, however, they show –descriptively- how a range of individual factors (all of which seem intuitively relevant) may readily give rise to complex interactions, and this makes it reasonable to expect interactions between these factors in people’s judgments in everyday life also.

 Set against these considerations, it seems striking how limited psychological research on these issues has been, not just in the climate context, but within psychology more generally. There have been many studies on source reliability and persuasion in the context of single communicators (Petty & Caccioppo, 1994; Birnbaum & Stegner, 1979; see Eagly & Chaiken, 1994 and Pornitpitkan, 2004 for reviews), there have been a few studies of the impact of coherence (e.g., Harris & Hahn, 2009) and the cited work on consensus (e.g., Kahan et al, 2011), and we know of one study that has concerned itself with source independence (Soll, 1999). But the models described suggests that any of this work will only have scratched the surface if interactions between these factors are not also considered.

 First and foremost, we thus think the material covered in this paper is relevant to improving empirical research aimed at lay people’s understanding of science. Specifically, it makes the case for a systematic programme of psychological research into reliability, independence, and coherence which can draw on the rich set of results philosophy has delivered. But, even in the absence of detailed experimental findings, it suggests reasonable assumptions about things that might improve science communication. Minimally, attention to the perceived reliability (for the target audience!) of the source communicating a level of consensus seems essential, and ways to include information relevant to judgments of reliability and independence of the scientists themselves should be explored. Finally, climate communication scholarship is sometimes presented as a dispute between 'information deficit advocates' who argue that getting more information to people about climate change is key and 'cultural cognition advocates' who have emphasised the role of cultural values in forming climate attitudes. Taking seriously the testimonial aspect of consensus communication (and the issue of source reliability it brings to the fore) suggests this may be a false dichotomy (see also Cook & Jacobs, 2014): beliefs about communicators are in many ways inseparable from an assessment of the evidence itself, and other, prior, beliefs are rationally relevant to both.

In the climate context, awareness of the high level of agreement among climate scientists has been dubbed a “gateway belief” (see e.g., Cook & Findlay, 2014) that influences beliefs about whether global warming is happening, its causes, and attitudes toward policy (Ding et al., 2011; McCright et al., 2013; Aklin & Urpelainen, 2014). On closer inspection, communicating the consensus as a strategy for public engagement on climate change is a much more complex proposition than it first appears. A simple statement about consensus hides multiple complex and overlapping evidential signifiers, including but not limited to the reliability of the communicator, the sources providing the consensus information, and their degree of independence. Given all of this, more can, and should, be done to make communication of consensus information effective.

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1. <http://whatweknow.aaas.org/get-the-facts/> [↑](#footnote-ref-1)
2. This model assumes the expertise component of Table 1. Trustworthiness is not captured separately, though experts are also allowed to be biased in whether or not they provide a positive report. [↑](#footnote-ref-2)
3. These models are ‘simple’ both in that one might need to consider, in real world contexts, yet more fine-grained decomposition of the factors influencing source reliability (see e.g., Harris et al., in press) and they are simple in that it has been argued that there may be further types of uncertainty both in general (e.g., Schum, 1994) and in the climate context specifically (e.g., Millner, Dietz & Heal, 2012; Thagard & Findlay, 2014) that are ‘beyond’ Bayesian probability. [↑](#footnote-ref-3)